Some Monte Carlo Evidence for Adaptive Estimation of Unit-Time Varying Heteroscedastic Panel Data Models

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Abstract

In this paper, we present an adaptive estimator for panel data model with unknown unit-time varying heteroscedastic error component of unknown form by using probability weighted moments rather than conventional kernel estimators already available in the literature and then evaluate the finite sample performance of the proposed estimator in terms of efficiency and testing of hypothesis. The Monte Carlo evidence suggests that the proposed estimator performs adequately under different data generated processes, especially for small samples that are the most practical situations.

Keyword: Adaptive estimator, Probability weighted moments, Heteroscedasticity, Unit-time varying error component

Introduction

An extensive literature is available on the issue of heteroscedasticity in the context of cross-section and time-series data and to deal this problem, especially, for heteroscedasticity of unknown form, there are many adaptive results using nonparametric methods; see Carroll (1982), Delgado (1992), Hidalgo (1992), Robinson (1987), among many others. But for panel data, referred as cross-section data sampled over different time period for the same economic agent, the issue of heteroscedasticity has not been studied as much extensively. In recent literature, only few references can be found so for; see Roy (1999), Baltagi (1998), Li and Stengos (1994), Baltagi and Griffin (1988), Randolph (1988), Mazodier and Trongnon (1978), etc. Randolph's work is based on unbalanced panel data while Baltagi and Griffin (1988) extend on Mazodier and Trongnon's work for the balanced case. Baltagi and Griffin (1988) consider heteroscedasticity coming in through the unit-specific error. They simply use an empirical example to provide some support for their estimators. Also the procedure proposed by them requires a large time component for the panel, which may not always be available. Li and Stengos (1994) provide an adaptive estimator for panel data models with unit-time varying heteroscedastic error component. Roy (1999) proposes an adaptive estimator for the estimation of panel models with unit-specific heteroscedastic error component by giving some Monte Carlo evidence to support the proposal and unlike the estimator proposed by Baltagi and Griffin (1988), there is no need for large time component.

In this paper, an adaptive procedure is formulated for the estimation of panel data model with unit-time varying heteroscedastic error component of unknown form by replacing the kernel estimator, presented by Li and Stengos (1994), with probability weighted moments, explained by Downton (1966) and Greenwood (1979) due to their robustness over conventional moments for more efficient inferences. Monte Carlo studies on the lines of Rilstone (1991), Li and Stengos (1994) and Roy (1999) are carried out to evaluate the performance of the estimator. Since Li and Stengos (1994) find the proposed estimator to perform adequately comparing it with different standard estimators so, in this paper, we just compare the new proposed estimator with the estimator given by Li and Stengos (1994). In section 2, we give unit-time varying heteroscedastic error component panel data model. In section 3, an adaptive estimator is proposed on the basis of probability weighted moments. In section 4, Monte Carlo experiment is carried out under two different data generating procedures to rank the performance of the adaptive estimator. In section 5, results and discussion are presented and also performance of the estimators is evaluated in testing of hypotheses. Finally, section 6 concludes.

Unit-time Varying Heteroscedastic Error Component Panel Data Model

A standard error component model, discussed by Hsiao (1985), Li and Stengos (1994), Baltagi (1995), and Roy (1999) among others is given as

$$y_{it} = x_{it}\beta + \mu_i + v_{it} \qquad (2.1)$$

where $i = 1, 2, \ldots, N; t = 1, 2, \ldots, T$, x_{it} is 1 x k, μ_i is the unit-specific error component with μ_{it} ~ $i.i.d.$ (0, σ_μ^2) while v_{it} is the unit-time varying error component and ~ $i.i.d.$(0, π_{ij}). Where $\pi_{ij} = \pi(x_{ij})$= Var (v_{it}) and shows that unit-time varying error component is heteroscedastic.

The vector-matrix form of (2.1) can be

$$y = x\beta + Z\mu + v \qquad (2.2)$$

where $Z = I_N \otimes e_T$, e_T is a T dimensional column vector of ones and $\mu = [\mu_1, \mu_2, \ldots, \mu_N]'$. y and v are NT x 1 column vectors of the dependent variable and the unit-time varying error component, respectively while x is an NT x K matrix of repressors.

The inverse of the conditional variance-covariance matrix of the error term in (2.2) denoted by Ω^{-1}, following Baltagi and Griffin (1988) and Roy (1999), is given as

$$\Omega^{-1} = diag[1/\sigma_i^2] \otimes (J_T/T) + diag[1/\sigma_v^2] \otimes (I_T - J_T/T) \qquad (2.3)$$

where $\sigma_i^2 = T\omega_i + \sigma_v^2$ $\forall$ i and J_T is a square matrix of ones of dimension T.

The true GLS estimator of β is

$$\tilde{\beta} = (x'\Omega^{-1}x)^{-1} x'\Omega^{-1} y \qquad (2.4)$$

Since (2.4) involves working with a *NT* x *NT* *(Ω^{-1})* matrix which can be quite demanding if one has a large data set so (2.4) can be rewritten as

$$\tilde{\beta} = \left(\sum_{i=1}^{N} x'_i B_i^{-1} x_i\right)^{-1} \left(\sum_{i=1}^{N} x'_i B_i^{-1} y_i\right) \qquad (2.5)$$

where x_i is a *T* x *K* matrix of repressors for the *i*-th individual, y_i is *T* x 1 and B_i^{-1} is given as

$$B_i^{-1} = \frac{1}{\gamma_i(1-\rho_i)}\left[I_T - \frac{e_T e_T' \rho_i}{(1-\rho_i+T\rho_i)}\right] \qquad (2.6)$$

with $\rho_i = \sigma_\mu^2 / \gamma_i$ and $\gamma_i = \sigma_\mu^2 + \pi_{ij}$ (the total variance) (2.7)

Adaptive Estimator

To obtain the Estimated Generalized Least Squares (EGLS) of β (as in 2.5), we need to estimate ρ_i and γ_i given in (2.6). Following Hsiao (1986) and Li and Stengos (1994), σ_μ^2 can be estimated as

$$\hat{\sigma}_\mu^2 = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T} \hat{\mu}_{it}\hat{\mu}_{i,t-1}}{N(T-1)} \qquad (3.1)$$

where $\hat{\mu}_{it}$ is the OLS residual.

Li and Stengos (1994) and Roy (1999) propose a kernel estimator of γ_i as

$$\hat{\gamma}_i = \frac{\sum_{j=1}^{N}\sum_{t=1}^{T} \hat{\mu}_{jt}^2 K\left(\frac{\bar{x}_i - x_{jt}}{h}\right)}{\sum_{j=1}^{N}\sum_{t=1}^{T} K\left(\frac{\bar{x}_i - x_{jt}}{h}\right)} \qquad (3.2)$$

where *K(.)* is the kernel function as $K(\varphi_{it}) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{\varphi_{it}^2}{2}\right)$ with *h* as the smoothing parameter. Then after obtaining the estimate of γ_i, the estimate of π_{ij} can be obtained as $\hat{\pi}_{it} = \hat{\gamma}_i - \hat{\sigma}_\mu^2$ and then after calculating $\hat{\rho}_i = \hat{\sigma}_\mu^2 / \hat{\gamma}_i$, the estimate of β (2.5) can be achieved.

But in this paper, we present an adaptive estimator in the presence of unit-time varying heteroscedastic error component by estimating Var(v_{it}) = π_{ij} using probability weighted moments discussed by Downton (1966) as linear estimate of the standard deviation of the normal distribution as

$$S_{pw} = \frac{\sqrt{\pi}}{n}\sum_{i=1}^{n}\left[Y_i - 2\left(1 - \frac{i-0.5}{n}\right)Y_i\right] \qquad (3.3)$$

For our problem

$$\hat{\pi}_{it} = [\frac{\sqrt{\pi}}{i} \sum_{i=1}^{N} \{y_{(it)} - 2(1 - \frac{i-0.5}{N}) y_{(it)}\}]^2 \quad (3.4)$$

where $y_{(it)}$ are the ordered observations and *(i-0.5)/N* is the empirical distribution function $F_N(Y)$.

Now the adaptive estimator can be given by reformulating (2.5) as

$$\hat{\beta} = (\sum_{i=1}^{N} x'_i \hat{\tau}_i^{-1} x_i)^{-1} (\sum_{i=1}^{N} x'_i \hat{\tau}_i^{-1} y_i) \quad (3.5)$$

where

$$\hat{\tau}_i^{-1} = \frac{1}{\hat{\gamma}_i (1-\hat{\rho}_i)} \left[I_T - \frac{e_T e_T^{/} \hat{\rho}_i}{(1-\hat{\rho}_i + T\hat{\rho}_i)} \right] \quad (3.6)$$

Monte Carlo Experiment

In this section, Monte Carlo experiment is carried out to study the performance of the proposed estimator. For comparative purposes, the design of the Monte Carlo experiment is as same as used by Rilstone (1991), Li and Stengos (1994), and Roy (1999). The following model is considered:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \mu_i + v_{it}; \quad i = 1, 2, \ldots, N; t = 1, 2, \ldots, T \quad (4.1)$$

where $x_{it} = 0.5\omega_{i,t-1} + \omega_{it}$ and ω_{it} is generated by two different data generating processing (DGP), namely

DGP-I: $\omega_{it} \sim i.i.d.\ U(0, 2)$,
DGP-II: $\omega_{it} \sim i.i.d.\ e^{v_{it}}$ and v_{it} *i.i.d.* $N(0, (0.4)^2)$ i.e., ω_{it} is Lognormal.

The parameters β_0 and β_1 are assigned the values 5 and 0.5, respectively and μ_i*s* are generated as $\mu_i \sim N(0, \sigma_\mu^2)$. We generate v_{it} as $v_{it} \sim i.i.d.\ N(0, \pi_{ij})$. Where π_{ij} = Var (v_{it}) = $\pi(x_{ij})$ shows that unit-time varying error component is heteroscedastic and $\pi(x_{ij}) = \alpha^2(1 + \lambda\ x_{it})^2$. Let $\bar{\pi} = E(\pi(x))$, denotes the expected variance of v_{it}. On the lines of Li and Stengos (1994), we fix the total variance $\gamma_i = \sigma_\mu^2 + \bar{\pi} = 8$ and define $\rho = \sigma_\mu^2 / (\sigma_\mu^2 + \bar{\pi})$, where ρ takes values, 0.2, 0.5, and 0.8. For each fixed value of ρ, the value of σ_μ^2 is calculated to vary the share of the variance of the unit-specific error term in the total variance. For each fixed value of ρ and σ_μ^2, λ is assigned values 0, 1, 2, and 3 where 0 denotes homoscedastic unit-time varying error while the degree of heteroscedasticity increases as the value of λ becomes larger. For a fixed σ_μ^2, a value of $\bar{\pi}$ is obtained (as $\bar{\pi} = 8 - \sigma_\mu^2$) using the different values of λ (*0, 1,* *2*, and *3*) and the values of α are chosen in such a way that the expected variance $\bar{\pi}$ is fixed for different values of λ. Then the values of ω_i are obtained for each σ_{μ}^{2} under the four different λ values. Following Roy (1999) and Li and Stengos (1994), the two schemes for sample sizes are used:

i) $N = 50$, $T = 3$; i.e., N X $T = 150$
ii) $N= 100$, $T= 3$; i.e., N X $T =300$

For the estimation part, the estimator proposed by Li and Stengos (1994), is evaluated on the same directions of Li and Stengos (1994), using the normal kernel and smoothing parameter values *h* (0.8, 1, 1.2) and this estimation is denoted as generalized least squares adaptive (GLSAD) estimation as named by Li and Stengos (1994). The proposed adaptive estimator (3.5) is determined and denoted as probability weighted generalized least squares (PWGLS).

Li and Stengos (1994) report the adequacy of the proposed GLSAD estimator by comparing it with different standard estimators i.e., OLS estimator, conventional GLS estimator of one-way error component model that assumes the remainder error term v_{it} is homoscedastic (GLSH), and WITHIN estimator. So in this section, the adaptive PWGLS estimator is just compared with the GLSAD estimator of Li and Stengos (1994) and the OLS estimator. For this purpose, the efficiency of PWGLS relatives to GLSAD and OLS is computed. The relative efficiency (R.E) is defined here as the ratio of the mean square of the estimator under consideration to the mean square error of PWGLS e.g., R.E = M.S.E (GLSAD)/M.S.E (PWGLS).

The efficiency of the estimators is not only concern while estimating the model (4.1) but performance of the hypothesis tests regarding the coefficients is also counted. To illustrate the impact of the both estimators on hypothesis testing, a test H_0: $\beta_1=0.5$ against $\beta_1 \neq 0.5$ is considered and the relevant *p*-values are computed. The larger *p*-value gives the statistical non-significance and indicates the stronger evidence for accepting the null hypothesis; $\beta_1=0.5$.

Results and Discussions

Table 1 gives the relative efficiency under DGP-I, with a sample size of 150, formed with N = 50, T = 3. It shows when $\lambda = 0$ then for all the cases of ρ = 0.2, 0.5, 0.8, both GLSAD estimator and the proposed PWGLS estimator perform almost with equal efficiency. In other words, when the unit-time varying error term is homoscedastic then one may use any one from the both estimators. But for all different values of ρ, the OLS estimator performs poorly and bears relatively great efficiency loss for smaller values of σ_{μ}^{2} (larger contribution of $\bar{\pi}$). The OLS estimator performs worse since it ignores both the effects of μ_i and v_{it}. When λ = 1, the PWGLS estimator performs well for all the cases of ρ = 0.2, 0.5, 0.8 but as the contribution of σ_μ^2 increases in the total variance the relative efficiency of the PWGLS estimator begin to decrease. That is for the larger role of $\overline{\pi}$ in the total variance, the proposed estimator becomes more attractive. For the higher degree of heteroscedasticity (λ = 2, 3), the PWGLS outperforms as compared to GLSAD and OLS. The sensitivity of the GLSAD estimator can be observed by the selection of the smoothing parameter *h*. Generally, for different values of *h* the GLSAD estimator varies in performance that also verifies the findings of Roy (1999) and Li and Stengos (1994) no such problem is faced for the use of PWGLS.

Table 2 gives the relative efficiency under DGP-I, with a sample size of 300, formed with N = 100, T = 3. The results in this table almost possess the same qualitative interpretations as that is in Table 1. The PWGLS performs quite adequately in all the cases as discussed above. It can again be noted that with the increase in sample size from 150 to 300, the efficiency of the PWGLS decreases, although in small amount. For example, In Table 1, for the case of ρ = 0.2 (and λ=1, 2, 3), the relative efficiency ranges from 1.0475 to 1.2514 that falls in 1.0067 to 1.2455 in Table 2. Similar decrease can be found in the cases when ρ = 0.5, 0.8. These results again signify the attractiveness of the PWGLS for small samples.

Table 3 and Table 4 show the relative efficiency under DGP-II where regressors are generated by lognormal distribution and the sample sizes are 150 and 300. The adaptive estimator PWGLS gives the results in the same fashion as under DGP-I. Efficiency benefits of the proposed estimator can be found for smaller values of ρ and σ_μ^2 (larger contribution of $\overline{\pi}$) almost in the same routine as discussed above.

The performance of the estimators in the hypothesis tests regarding the coefficients is also taken into account while estimating the model. Table 5 shows the *p*-values for testing the hypothesis H_0: β_1=0.5 against $\beta_1 \neq 0.5$ to see the impact of the both estimators, GLSAD and the proposed PWGLS under DGP-I with sample size 150. The larger *p*-value gives the statistical non-significance and indicates that there is no significant difference between the estimated value of slope coefficient and the parametric value 0.5 or, in other words, a stronger evidence for accepting the null hypothesis; β_1 = 0.5. The table reports that when λ = 0 then for all the cases of ρ = 0.2, 0.5, 0.8, both GLSAD estimator and the proposed PWGLS estimator perform almost equally in the sense of hypothesis testing. For λ = 1, the p-value falls around 0.97 for PWGLS and that is around 0.96 for GLSAD which means that the test is highly non-significant or there is no significance difference between the estimated slope value and the parametric (hypothesized) slope value. For

PWGLS there is stronger evidence to accept the null hypothesis as compared to GLSAD. In other words, the PWGLS estimates remain closer to the true value as compared to GLSAD estimates. This degree of non-significance increases with the increase of the degree of heteroscedasticity and in almost all the cases the p-value remains low for GLSAD when compared with that of the adaptive PWGLS estimator and same sensitivity of the smoothing parameter can also be found here. This also magnifies the adequacy of the proposed estimator even in testing of hypothesis.

Table 6 shows a different picture of p-values under DGP-I (sample size; 300) as in Table 5. For homoscedastic unit-time varying error term (λ=0), there is relatively high difference up to 0.05 between the p-values for the both estimators and PWGLS estimator bears high p-values. For λ = 1, p-values increase for the both estimators in large sample and remains to some extent high for PWGLS but for λ = 2 and λ = 3, generally, the p-values decline for PWGLS and rise for GLSAD. As it is previously discussed that for small sample PWGLS shows better performance as it does in large samples, generally, a similar behaviour for p-values is also observed in this table.

Table 7 and Table 8 show the p-values for testing the slope coefficient under DGP-II where regressors are generated by lognormal distribution and the sample sizes are 150 and 300. The results follow the same routine as they do in Table 5 and 6.

Conclusions

In this paper, following the work of Li and Stengos (1994) and Roy (1999), we present an adaptive estimator for panel data model with unit-time varying heteroscedasticity of unknown form by replacing kernel estimator, presented by Li and Stengos (1994), with probability weighted moment estimator. The Monte Carlo study under different data generating processes shows the adequate performance of the proposed estimator over the GLSAD estimator suggested by Li and Stengos (1994), specially for small samples and high degree of heteroscedasticity and while comparing with the tedious manipulations and sensitivity of the smoothing parameter in the GLSAD estimator. When one does not have any information on the degree of heteroscedasticity and the share of the different variances of the error terms in the total variance, which would indeed be the case with real data and from more applied point of view, it might be better to use PWGLS. Moreover, our proposed estimator PWGLS also performs with qualitative attractiveness for the hypothesis tests regarding the coefficients while estimating the model. Although, this performance is not very remarkable as compared to that of GLSAD estimator but yet relatively simple computations make it more desirable to use.

Table 1: Relative Efficiency of the Slope Coefficient: DGP-I, N = 50, T = 3

	λ = 0	λ = 1	λ = 2	λ = 3
		ρ = 0.2		
GLSAD(h = 0.8)	1.0094	1.0482	1.1180	1.2490
GLSAD(h = 1.0)	1.0082	1.0476	1.1174	1.2514
GLSAD(h = 1.2)	1.0080	1.0475	1.1168	1.2440
OLS	2.1358	3.3138	4.6565	5.3927
		ρ = 0.5		
GLSAD(h = 0.8)	1.0087	1.0319	1.1083	1.2116
GLSAD(h = 1.0)	1.0084	1.0303	1.1062	1.2144
GLSAD(h = 1.2)	1.0078	1.0320	1.1057	1.2068
OLS	1.5060	2.3076	2.7616	2.6960
		ρ = 0.8		
GLSAD(h = 0.8)	1.0041	1.0329	1.0907	1.1879
GLSAD(h = 1.0)	1.0035	1.0314	1.0884	1.1922
GLSAD(h = 1.2)	1.0035	1.0309	1.0880	1.1836
OLS	1.1010	1.3259	1.4622	1.5463

Table 2: Relative Efficiency of the Slope Coefficient: DGP-I, N = 100, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
		ρ = 0.2		
GLSAD(h = 0.8)	1.0481	1.0101	1.1168	1.2449
GLSAD(h = 1.0)	1.0476	1.0070	1.1159	1.2455
GLSAD(h = 1.2)	1.0475	1.0067	1.1153	1.2400
OLS	3.5777	2.3007	5.0926	5.9372
		ρ = 0.5		
GLSAD(h = 0.8)	1.0077	1.0295	1.1077	1.2071
GLSAD(h = 1.0)	1.0075	1.0280	1.056	1.2080
GLSAD(h = 1.2)	1.0068	1.0291	1.050	1.2020
OLS	1.5007	2.2854	2.7783	2.7163
		ρ = 0.8		
GLSAD(h = 0.8)	1.0036	1.0298	1.0890	1.1788
GLSAD(h = 1.0)	1.0029	1.0287	1.0863	1.1805
GLSAD(h = 1.2)	1.0024	1.0280	1.0858	1.1738
OLS	1.0995	1.3143	1.4331	1.5223

Table 3: Relative Efficiency of the Slope Coefficient: DGP-II, N = 50, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
		ρ = 0.2		
GLSAD(h = 0.8)	1.0078	1.0529	1.0922	1.1986
GLSAD(h = 1.0)	1.0064	1.0610	1.0910	1.998
GLSAD(h = 1.2)	0.9975	1.0558	1.1013	1.2054
OLS	1.9900	3.0817	4.2250	4.8019
		ρ = 0.5		
GLSAD(h = 0.8)	1.0079	1.0396	1.0770	1.1611
GLSAD(h = 1.0)	1.0055	1.0474	1.0742	1.1630
GLSAD(h = 1.2)	0.9954	1.0435	1.0869	1.1693
OLS	1.3992	2.1108	2.3968	2.3399
		ρ = 0.8		
GLSAD(h = 0.8)	1.0079	1.0252	1.0617	1.1434
GLSAD(h = 1.0)	1.0022	1.0237	1.0588	1.1466
GLSAD(h = 1.2)	1.0015	1.0234	1.0585	1.1543
OLS	1.0662	1.2823	1.3864	1.4503

Table 4: Relative Efficiency of the Slope Coefficient: DGP-II, N=100, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
		ρ = 0.2		
GLSAD(h = 0.8)	1.0073	1.0591	1.0925	1.1992
GLSAD(h = 1.0)	1.0024	1.0707	1.0897	1.1951
GLSAD(h = 1.2)	1.0031	1.0632	1.1054	1.2113
OLS	2.2910	3.5635	5.0615	5.8107
		ρ = 0.5		
GLSAD(h = 0.8)	1.0028	1.0423	1.0899	1.1748
GLSAD(h = 1.0)	1.0024	1.0548	1.0864	1.1698
GLSAD(h = 1.2)	1.0021	1.0463	1.0995	1.1886
OLS	1.4516	2.2511	2.7595	2.7047
		ρ = 0.8		
GLSAD(h = 0.8)	1.0018	1.0183	1.0668	1.1339
GLSAD(h = 1.0)	1.0007	1.0338	1.0619	1.1282
GLSAD(h = 1.2)	0.9840	1.0231	1.0831	1.1500
OLS	1.0728	1.2972	1.3604	1.4514

Table 5: P-Value for testing H_0: $\beta_1=0.5$ against $\beta_1 \neq 0.5$: DGP-I, N=50, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
		$\rho = 0.2$		
PWGLS	0.9569	0.9783	0.9748	0.9758
GLSAD(h = 0.8)	0.9400	0.9667	0.9645	0.9566
GLSAD(h = 1.0)	0.9362	0.9618	0.9689	0.9612
GLSAD(h = 1.2)	0.9382	0.9689	0.9679	0.9603
		$\rho = 0.5$		
PWGLS	0.9602	0.9606	0.9863	0.9758
GLSAD(h = 0.8)	0.9688	0.9533	0.9583	0.9585
GLSAD(h = 1.0)	0.9698	0.9569	0.9521	0.9521
GLSAD(h = 1.2)	0.9697	0.9548	0.9511	0.9508
		$\rho = 0.8$		
PWGLS	0.9726	0.9731	0.9717	0.9711
GLSAD(h = 0.8)	0.9734	0.9625	0.9548	0.9609
GLSAD(h = 1.0)	0.9814	0.9650	0.9437	0.9564
GLSAD(h = 1.2)	0.9782	0.9674	0.9420	0.9543

Table 6: P-Value for testing H_0: $\beta_1=0.5$ against $\beta_1 \neq 0.5$: DGP-I, N=100, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
		$\rho = 0.2$		
PWGLS	0.9833	0.9992	0.9906	0.9920
GLSAD(h = 0.8)	0.9336	0.9899	0.9806	0.9752
GLSAD(h = 1.0)	0.9341	0.9927	0.9829	0.9775
GLSAD(h = 1.2)	0.9426	0.9876	0.9778	0.9722
		$\rho = 0.5$		
PWGLS	0.9653	0.9767	0.9995	0.9925
GLSAD(h = 0.8)	0.9822	0.9735	0.9606	0.9577
GLSAD(h = 1.0)	0.9830	0.9778	0.9556	0.9531
GLSAD(h = 1.2)	0.9813	0.9727	0.9545	0.9520
		$\rho = 0.8$		
PWGLS	0.9675	0.9866	0.9675	0.9604
GLSAD(h = 0.8)	0.9695	0.9829	0.9543	0.9679
GLSAD(h = 1.0)	0.9774	0.9820	0.9467	0.9616
GLSAD(h = 1.2)	0.9746	0.9866	0.9443	0.9588

Table 7: P-Value for testing H$_0$: β_1=*0.5* against $\beta_1 \neq$ *0.5*: DGP-II, N=50, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
ρ = 0.2				
PWGLS	0.9573	0.9457	0.9384	0.9425
GLSAD(h = 0.8)	0.9483	0.9359	0.9341	0.9239
GLSAD(h = 1.0)	0.9423	0.9417	0.9320	0.9279
GLSAD(h = 1.2)	0.9466	0.9365	0.9294	0.9309
ρ = 0.5				
PWGLS	0.9334	0.9508	0.9554	0.9441
GLSAD(h = 0.8)	0.9294	0.9406	0.9392	0.9070
GLSAD(h = 1.0)	0.9320	0.9443	0.9413	0.9106
GLSAD(h = 1.2)	0.9387	0.9453	0.9454	0.9115
ρ = 0.8				
PWGLS	0.9578	0.9618	0.9400	0.9322
GLSAD(h = 0.8)	0.9456	0.9488	0.9070	0.9054
GLSAD(h = 1.0)	0.9464	0.9530	0.9109	0.9140
GLSAD(h = 1.2)	0.9464	0.9583	0.9120	0.9150

Table 8: P-Value for testing H$_0$: β_1=*0.5* against $\beta_1 \neq$ *0.5*: DGP-II, N=100, T=3

	λ = 0	λ = 1	λ = 2	λ = 3
ρ = 0.2				
PWGLS	0.9693	0.9878	0.9813	0.9867
GLSAD(h = 0.8)	0.9505	0.9646	0.9767	0.9701
GLSAD(h = 1.0)	0.9472	0.9635	0.9695	0.9728
GLSAD(h = 1.2)	0.9618	0.9742	0.9720	0.9861
ρ = 0.5				
PWGLS	0.9589	0.9867	0.9839	0.9792
GLSAD(h = 0.8)	0.9376	0.9654	0.9805	0.9577
GLSAD(h = 1.0)	0.9377	0.9715	0.9823	0.9574
GLSAD(h = 1.2)	0.9382	0.9599	0.9839	0.9576
ρ = 0.8				
PWGLS	0.9531	0.9765	0.9721	0.9618
GLSAD(h = 0.8)	0.9503	0.9573	0.9694	0.9448
GLSAD(h = 1.0)	0.9802	0.9561	0.9690	0.9483
GLSAD(h = 1.2)	0.9823	0.9645	0.9714	0.9452

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