Robust estimation procedure in panel data model

Nurul Sima Mohamad Shariff and Nor Aishah Hamzah

Citation: AIP Conference Proceedings **1602**, 1085 (2014); doi: 10.1063/1.4882619
View online: http://dx.doi.org/10.1063/1.4882619
View Table of Contents: http://scitation.aip.org/content/aip/proceeding/aipcp/1602?ver=pdfcov
Published by the AIP Publishing

Robust Estimation Procedure in Panel Data Model

Nurul Sima Mohamad Shariff[a] and Nor Aishah Hamzah[b]

[a]*Faculty of Science of Technology, Universiti Sains Islam Malaysia (USIM)*
71800, Nilai, Negeri Sembilan, Malaysia
[b]*Institute of Mathematical Sciences, Universiti Malaya*
50630, Kuala Lumpur, Malaysia

Abstract. The panel data modeling has received a great attention in econometric research recently. This is due to the availability of data sources and the interest to study cross sections of individuals observed over time. However, the problems may arise in modeling the panel in the presence of cross sectional dependence and outliers. Even though there are few methods that take into consideration the presence of cross sectional dependence in the panel, the methods may provide inconsistent parameter estimates and inferences when outliers occur in the panel. As such, an alternative method that is robust to outliers and cross sectional dependence is introduced in this paper. The properties and construction of the confidence interval for the parameter estimates are also considered in this paper. The robustness of the procedure is investigated and comparisons are made to the existing method via simulation studies. Our results have shown that robust approach is able to produce an accurate and reliable parameter estimates under the condition considered.

Keywords: Cross Sectional Dependence, Outliers, Robust Method, and Panel Data
PACS: 02.50.Tt, 05.10.Ln, 05.45.Tp

INTRODUCTION

There are vast numbers of studies on panel data modeling in the presence of cross sectional dependence [1-8]. This is due to the recent development in panel data analysis in view of the fact that most economic data are cross-correlated in panel framework. The presence of contemporaneous cross correlation among the disturbances, finds support from many empirical applications in macroeconomics, finance and international finance [4]. Many studies have been conducted by characterising cross sectional dependence (CD) using factor structure [1-3]. In order to correct CD in modeling and estimating the panel, Coakley et al. [1] and Stock and Watson [9] proposed the principal component approach to obtain unobserved factor in order to accommodate the presence of CD in the panel. Kapetonis and Pesaran [5] applied the principal component procedure in modeling the standard Arbitrage Pricing Theory Model of the company asset returns. Bai and Ng [2] and Moon and Perron [4] determined the number of such unobserved factors using the selection criteria such as the Akaike's information criterion (AIC) and Bayesian information criterion (BIC). This approach however, provides unreliable parameter estimates since the residuals are obtained from the procedures based on the Ordinarily Least Squares (OLS) method to explain the CD. Due to this interest, the techniques used to estimate the panel data model, both with and without the presence of cross sectional dependence are discussed in this paper. These techniques include the standard method that uses OLS and the proposed procedure that is based on robust parameter estimation. The properties of the proposed estimator are derived. Then, a robust confidence interval for the parameter estimates is constructed. Subsequently, the reliability and accuracy of the proposed method are investigated via Monte Carlo simulation study.

COMMON CORRELATED EFFECTS MEAN GROUP (CMG)

In order to correct for cross sectional dependence, Pesaran [7] introduced two approaches of the common correlated effects in modeling the panel; namely, (1) Common Correlated Effects Mean Group Estimators (CMG), and (2) Pooled version of the common correlated effects where the parameters of interest are assumed constant for all cross-sectional units. In the presence of CD, the following model is considered:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i^T \mathbf{x}_{it} + \gamma_i^T f_t + \varepsilon_{it} \tag{1}$$

where y_{it} denotes the observation on the i^{th} cross section unit at time t for $i = 1,2,...,N$; and $t = 1,2,...,T$, $\mathbf{x}_{it}$ is a $k \times 1$ vector of independent variable on the i^{th} cross section unit at time t. Here, α_i, $\boldsymbol{\beta}_i$ are parameters which differ across i, while f_t is the unobserved factor, γ_i are the factor loadings which are common across i, and ε_{it} represents random error. In order to eliminate the effect of CD, Pesaran [7] used the cross section

Proceedings of the 3rd International Conference on Mathematical Sciences
AIP Conf. Proc. 1602, 1085-1090 (2014); doi: 10.1063/1.4882619

averages of the dependent variable ($\bar{y}_t$) and observed regressor ($\bar{\mathbf{x}}_t$), to explain the unobserved factor, f_t. Here, $\boldsymbol{\beta}_i$ can be estimated consistently by augmenting the dependent variable; y_{it} on the observed regressor; $\mathbf{x}_{it}$ with vector of ones and cross section averages of respective dependent and observed variable $\bar{y}_t, \bar{\mathbf{x}}_t$; using OLS. Therefore, the individual parameter estimate of the common correlated effects in (1) is given by:

$$\hat{\boldsymbol{\beta}}_i = (\mathbf{X}_i^T \mathbf{M} \mathbf{X}_i)^{-1} \mathbf{X}_i^T \mathbf{M} \mathbf{y}_i \quad (2)$$

where $\mathbf{M} = \mathbf{I}_t - \overline{\mathbf{H}}\left(\overline{\mathbf{H}}^T \overline{\mathbf{H}}\right)^{-1} \overline{\mathbf{H}}^T$ and $\mathbf{I}_t$ is a unit matrix of order $T \times T$. To compute factor loading γ, $\overline{\mathbf{H}} = (\mathbf{1}, \overline{\mathbf{X}}_t, \bar{y}_t)$ is used, where $\overline{\mathbf{H}}$ is a combination of vector of ones, average of independent variables$(\bar{\mathbf{x}}_t)$ and dependent variables $(\bar{y}_t)$. The CMG estimates, $\hat{\boldsymbol{\beta}}_{CMG}$ is then computed by averaging $\hat{\boldsymbol{\beta}}_i$ over N that is $\hat{\boldsymbol{\beta}}_{CMG} = \sum_{i=1}^{N} \hat{\boldsymbol{\beta}}_i / N$. Following Pesaran [7], the asymptotic distribution of CMG is $\sqrt{N}\left(\hat{\boldsymbol{\beta}}_{CMG} - \boldsymbol{\beta}\right) \xrightarrow{d} N\left(0, \hat{\boldsymbol{\Sigma}}_{CMG}\right)$ as $(N,T) \to \infty$ with $\xrightarrow{d}$ denotes convergence in distribution; and

$$\hat{\boldsymbol{\Sigma}}_{CMG} = \frac{\sum_{i=1}^{N} (\hat{\boldsymbol{\beta}}_i - \hat{\boldsymbol{\beta}}_{CMG})(\hat{\boldsymbol{\beta}}_i - \hat{\boldsymbol{\beta}}_{CMG})^T}{N-1}. \quad (3)$$

The CMG seems to be robust and stands out for homogeneous as well as heterogeneous slope experiments, and does not seem to depend on whether the rank condition is satisfied [7]. Coakley et al. [6] found that the CMG estimator stands out as the most robust in the sense that it is the preferred choice in rather general (non) stationary settings where regressors and errors share common factors and their factor loadings are possibly dependent. This procedure however has limitation where it is influenced by the outliers' effects since the OLS is used to model the data. A single influential outlier will automatically pull the fitted line towards it and result in poor parameter estimates. The standard error of CMG estimates is observed as lack robustness of standard deviation due to OLS estimated residuals. Moreover, there is the influence of the outlying observation on the mean and the corresponding $\mathbf{M}$. Due to such problem, the aim of this study is to limit the influence of outliers and this can be achieved through the use of robust measures. Thus, a robust version of RCMG is proposed in the next subsection.

ROBUST ESTIMATION PROCEDURE (RCMG)

Following Peter et al. [10] a general version of the M-estimator criterion for model (1) can be written as:

$$\min_{\boldsymbol{\beta}_i} \sum_{t=1}^{T} \hat{\sigma}_i u_i(\mathbf{x}_{it}) v_i^2(\mathbf{x}_{it}) \rho_i\left(\frac{\hat{e}_{it}(\boldsymbol{\beta}_i)}{\hat{\sigma}_i v_i(\mathbf{x}_{it})}\right) \text{ for each } i = 1,2,\ldots,N. \quad (4)$$

where $v_i(\mathbf{x}_{it})$ and $u_i(\mathbf{x}_{it})$ are positive functions that are related to the position of the $\mathbf{x}_{it}$ in the $\mathbf{X}$-space. Here, $\rho(\mathrm{t})$ is a differential convex function (with minimum at 0) and is known as the robustifying criterion function while $\hat{\sigma}_i$ is the robust scale. The objective function in (4) is introduced with the aim of minimizing a function related to standardized residuals. By using a weight function given by $w(t) = \frac{\psi(t)}{t}$, (4) is minimized by differentiating ρ_i with respect to $\boldsymbol{\beta}_i$ and yields

$$\sum_{t=1}^{T} u_i(\mathbf{x}_{it}) w_i\left(\frac{\hat{e}_{it}(\boldsymbol{\beta}_i)}{\hat{\sigma}_i v_i(\mathbf{x}_{it})}\right) \hat{e}_{it}(\boldsymbol{\beta}_i) \mathbf{x}_{it} = 0 \quad (5)$$

Several different robust M-estimators can be obtained by substituting the different choices of $u_i(\mathbf{x}_{it})$, $v_i(\mathbf{x}_{it})$ and $\psi_i(\mathbf{x}_{it})$. The choice will result in how much the data are scarified to achieve certain efficiency at the true underlying model assumption.

In order to provide robustness to the effects of the outlying observation occurring in the $\mathbf{X}$ and $\mathbf{y}$ directions, the high breakdown point estimator is suggested. Let $z_{it} = d_i(\mathbf{x}_{it}) \frac{\hat{e}_{it}(\boldsymbol{\beta}_i)}{\hat{\sigma}_i}$, and following the work of

Hung et. al [11], a generalization of the M-estimator can be obtained by substituting $u_i(\mathbf{x}_{it})=1$ and $v_i(\mathbf{x}_{it})=\dfrac{1}{d_i(\mathbf{x}_{it})}$ in (5), yields the following:

$$\sum_{t=1}^{T} w_i(z_{it})\hat{e}_{it}\mathbf{x}_{it} = 0 . \tag{6}$$

The $d_i(\mathbf{x}_{it})$ is given as a measure of the outlyingness "$\mathbf{X}$" from its mean value and is defined as follows:

Case I: single regressor variable: $d(\mathbf{x}_{it})=\dfrac{|\mathbf{X}_{it}-\mu_{\mathbf{X}}|}{\sigma_{\mathbf{X}}}$, where $\mu_{\mathbf{X}}$ is a robust location of $\mathbf{x}_i$ (median($\mathbf{x}_{it}$)) and $\sigma_{\mathbf{X}}$ is a robust scale (MAD) and is given by $\sigma_{\mathbf{X}}=1.4825\ \underset{t}{\text{median}}\left|\mathbf{x}_{it}-\underset{t}{\text{median}}(\mathbf{x}_{it})\right|$. Case II: multiple regressors: $d(\mathbf{x}_{it})=\sqrt{(\mathbf{x}_{it}-\mu_{\mathbf{X}})^T\mathbf{V}^{-1}(\mathbf{x}_{it}-\mu_{\mathbf{X}})}$, where $\mu_{\mathbf{X}}$ is a robust location of $\mathbf{x}_{it}$ (median ($\mathbf{x}_{it}$)) and $\mathbf{V}$ is a matrix of robust variance covariance matrix of $\mathbf{x}_{it}$ (Minimum Volume Ellipsoid). Following the procedure to the residuals of Bai and Ng [2], we have

$$\hat{\mathbf{e}}_i=\mathbf{M}\left(\mathbf{y}_i-\hat{\boldsymbol{\beta}}_i^T\mathbf{X}_i\right) \tag{7}$$

where $\hat{\mathbf{e}}_i$ is the fitted value of $\mathbf{e}_i$, for $i=1,2,\ldots,N$ of model (1), and $\mathbf{M}$ is computed as:

$$\mathbf{M}=\mathbf{I}_t-\overline{\mathbf{H}}\left(\overline{\mathbf{H}}^T\overline{\mathbf{H}}\right)^{-1}\overline{\mathbf{H}}^T . \tag{8}$$

In order to limit the influence of outliers in $\mathbf{M}$, the robust version given by $\mathbf{M}^*=\mathbf{I}_t-\overline{\mathbf{H}}^*\left(\overline{\mathbf{H}}^{*T}\overline{\mathbf{H}}^*\right)^{-1}\overline{\mathbf{H}}^{*T}$ is introduced; $\mathbf{I}_t$ is an identity T by T matrix with the value of $\overline{\mathbf{H}}^*=\left(1,\psi(\overline{\mathbf{X}}_t),\psi(\overline{\mathbf{y}}_t)\right)$. Here $\psi(.)$ are some filter functions for the adjusted value of location for dependent and independent variables. The values of $\psi(.)$ are set as follows:

$$\psi(\bar{y}_t)=\begin{cases}\bar{y}_t & ;\text{if } |\bar{y}_t|\le \text{c}\\ sign(\bar{y}_t)\times\left|\underset{i}{\text{median}}(y_{1t},.......,y_{Nt})\right| & ;\text{elsewhere}\end{cases} \tag{9}$$

where c is the critical value, chosen to achieve specified level of efficiency, and it is computed as $3\hat{\sigma}_{\bar{y}_t}$ with $\hat{\sigma}_{\bar{y}_t}$ is a robust scale given by $\hat{\sigma}_{\bar{y}_t}=1.4825\ \underset{t}{\text{median}}\left|\bar{y}_t-\underset{t}{\text{median}}(\bar{y}_t)\right|$. By substituting $\hat{\mathbf{e}}_i=\mathbf{M}^*\left(\mathbf{y}_i-\hat{\boldsymbol{\beta}}_i^T\mathbf{X}_i\right)$ in (7), (6) can be written as

$$\mathbf{X}_i^T\mathbf{M}^*\mathbf{W}_i(z_{it})\left(\mathbf{y}_i-\mathbf{X}_i\hat{\boldsymbol{\beta}}_i\right)=0 \tag{10}$$

and yields the final estimates of $\boldsymbol{\beta}_i$:

$$\hat{\boldsymbol{\beta}}_i=(\mathbf{X}_i^T\mathbf{G}_i\mathbf{X}_i)^{-1}\mathbf{X}_i^T\mathbf{G}_i\mathbf{y}_i \tag{11}$$

where $\mathbf{G}_i=\mathbf{M}^*\ \mathbf{W}_i(z_{it})$. $\hat{\boldsymbol{\beta}}_{RCMG}$ is then computed as $\hat{\boldsymbol{\beta}}_{RCMG}=\sum_{i=1}^{N}\hat{\boldsymbol{\beta}}_i/N$.

Inferences

The asymptotic distribution of the proposed estimator can be derived using several assumptions that are defined as follows: (i) the residuals in (1) are independent and identically (iid) normal distribution with mean zero and constant variance. (ii) the regressors are uncorrelated with the residuals. (iii) the unobserved factor, f_t and factor loadings, γ_i is iid for all i and t, and (iv) ρ_i in (4) are $\rho_i\left(\dfrac{\hat{e}_{it}}{\hat{\sigma}_i}\right)\ge 0$ and $\rho_i(0)=0$.

Hence, $\hat{\boldsymbol{\beta}}_i$ is found to be distributed with normal distribution with mean $\boldsymbol{\beta}_i$ and variance $\dfrac{\mathbf{v}_i}{\sqrt{T}}$ for $i=1,2,\ldots,N$; where

$$\mathbf{v}_i = \left(\mathbf{X}_i^T \mathbf{M}^* \mathbf{X}_i\right)^{-1} \hat{\sigma}_i^{\,2} \frac{E\left(\psi_i\left(\frac{\hat{e}_{it}(\boldsymbol{\beta}_i)}{\hat{\sigma}_i v_i(\mathbf{x}_{it})}\right)\right)^2}{\left(E\left(\psi_i'\left(\frac{\hat{e}_{it}(\boldsymbol{\beta}_i)}{\hat{\sigma}_i v_i(\mathbf{x}_{it})}\right)\right)\right)^2} \text{ and } v_i(\mathbf{x}_{it}) = \frac{1}{d_i(\mathbf{x}_{it})} \tag{12}$$

Other studies on inferences of parameter estimates can be found in Kapetonis and Pesaran [5] and Pesaran [7].

Confidence Interval

The $(1-\alpha)\times 100\%$ confidence interval (CI) for $\hat{\beta}_{RCMG}$ may be constructed by using the variance of $\hat{\beta}_{RCMG}$, $\mathbf{v}_i$ in (12) on which it is defined as:

$$\hat{\beta}_{RCMG} \pm t_{\alpha/2,n-p}\, se\left(\hat{\beta}_{RCMG}\right) \tag{13}$$

where $se\left(\hat{\beta}_{RCMG}\right) = \frac{1}{\sqrt{T}}\left(\hat{\Sigma}_{RCMG}\right)^{1/2}$ and $\hat{\Sigma}_{RCMG} = \frac{1}{N^2}\sum_{i=1}^{N}\mathbf{v}_i$.

FINITE SAMPLE BEHAVIOUR OF THE PROCEDURE

In this section, a Monte Carlo simulation study is run in order to obtain an approximate 95% confidence interval for the CMG and RCMG estimators. The following data generating process is considered in this study: $y_{it} = \alpha_i + \beta_i^T x_{it} + e_{it}$; and $e_{it} = \gamma_i^T f_t + \sigma_{it}\varepsilon_{it}$; with $\alpha_i \sim iidU(-0.5,0.5)$; $\sigma_{it} = 1$; $x_{it} \sim iidN(0,1)$; $\varepsilon_{it} \sim iidN(0,1)$; $f_t \sim iidN(0,1)$; and $\beta_i = \beta = 1.0$. Here, γ_i is set as follows: (i) $\gamma_i = 0$ for no cross sectional dependence; (ii) $\gamma_i \sim iidU(0.1,0.3)$ for mild cross sectional dependence and (iii) $\gamma_i \sim iidU(0.5,1.5)$ for strong effect of cross sectional dependence. In the presence of contaminations at time $t = \tau_i$, the residual takes the following form: $e_{it} = \begin{cases} e_{it} & \text{for } t \neq \tau_i \\ e_{it} + m_{it} & \text{for } t = \tau_i \end{cases}$ for $i = 1,2,\ldots,N;$ with $m_{it} \sim LN(1,2)$ and 5% contamination are chosen. The sample size is $N = (20,30,50)$ and $T = (20,30,50,100,200)$ with 1000 runs in uncontaminated and contaminated panels.

Results and Discussion

The CI of the parameter estimates for the respective estimator (CMG and RCMG) is reported in Tables 1 and 2. In uncontaminated panel (Table 1), the length of the CI of $\hat{\beta}_{CMG}$ attains a small value as N and T increases when no CD is present, mild CD and strong CD effect. Similar findings are observed for $\hat{\beta}_{RCMG}$ in all CD cases. For contaminated panel and without the presence of CD (row 1, Table 2), $\hat{\beta}_{CMG}$ yields a larger length of CI for $(N,T) = (20,20)$, but the length decreases as N and T increases. The CI of $\hat{\beta}_{CMG}$ however worsens under the presence of CD. The parameter estimates $\hat{\beta}_{RCMG}$ however provides better results for small N and T , and these values improve with shorter length of CI as N and T increases. This indicates that the robustness of $\hat{\beta}_{RCMG}$ in the presence of outliers in the panel.

TABLE (1): A CI of $\hat{\beta}_{CMG}$ and $\hat{\beta}_{RCMG}$ in Uncontaminated Panel

	$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$		$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$		$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$	
	CI	L	CI	L	CI	L	CI	L	CI	L	CI	L
T/N	**20**				**30**				**50**			
					$\gamma_i = 0$							
20	(0.879,1.113)	0.235	(0.859,1.143)	0.284	(0.910,1.096)	0.185	(0.883,1.116)	0.233	(0.924,1.069)	0.144	(0.925,1.096)	0.171
30	(0.916,1.081)	0.165	(0.884,1.104)	0.221	(0.931,1.071)	0.140	(0.910,1.090)	0.180	(0.939,1.055)	0.116	(0.918,1.071)	0.153
50	(0.932,1.063)	0.131	(0.923,1.104)	0.181	(0.944,1.057)	0.113	(0.932,1.071)	0.139	(0.955,1.048)	0.092	(0.948,1.038)	0.090
100	(0.955,1.041)	0.087	(0.948,1.057)	0.109	(0.966,1.034)	0.073	(0.956,1.038)	0.082	(0.969,1.028)	0.060	(0.965,1.029)	0.064
200	(0.964,1.031)	0.067	(0.962,1.029)	0.067	(0.975,1.026)	0.051	(0.961,1.036)	0.075	(0.978,1.018)	0.040	(0.978,1.029)	0.052
					$\gamma_i \sim iidU(0.1,0.3)$							
20	(0.889,1.116)	0.226	(0.862,1.134)	0.272	(0.907,1.089)	0.182	(0.887,1.116)	0.229	(0.922,1.071)	0.149	(0.921,1.118)	0.197
30	(0.904,1.079)	0.184	(0.888,1.106)	0.219	(0.924,1.072)	0.148	(0.909,1.089)	0.180	(0.942,1.058)	0.116	(0.921,1.087)	0.165
50	(0.923,1.070)	0.147	(0.918,1.085)	0.167	(0.940,1.045)	0.105	(0.935,1.062)	0.126	(0.957,1.041)	0.084	(0.955,1.041)	0.085
100	(0.954,1.050)	0.096	(0.943,1.053)	0.110	(0.964,1.036)	0.072	(0.944,1.038)	0.094	(0.971,1.027)	0.055	(0.960,1.036)	0.076
200	(0.967,1.032)	0.065	(0.965,1.046)	0.081	(0.974,1.025)	0.051	(0.966,1.032)	0.066	(0.980,1.020)	0.040	(0.978,1.024)	0.045
					$\gamma_i \sim iidU(0.5,1.5)$							
20	(0.891,1.117)	0.226	(0.863,1.139)	0.276	(0.910,1.086)	0.176	(0.889,1.117)	0.228	(0.923,1.068)	0.146	(0.913,1.119)	0.206
30	(0.908,1.092)	0.184	(0.892,1.099)	0.208	(0.924,1.071)	0.147	(0.910,1.091)	0.181	(0.943,1.055)	0.112	(0.925,1.078)	0.154
50	(0.922,1.068)	0.146	(0.912,1.084)	0.172	(0.945,1.056)	0.111	(0.928,1.069)	0.142	(0.961,1.045)	0.084	(0.951,1.043)	0.092
100	(0.956,1.051)	0.094	(0.943,1.054)	0.111	(0.961,1.040)	0.080	(0.946,1.034)	0.088	(0.972,1.026)	0.054	(0.962,1.034)	0.075
200	(0.966,1.032)	0.065	(0.963,1.042)	0.079	(0.974,1.023)	0.050	(0.969,1.027)	0.058	(0.980,1.022)	0.041	(0.979,1.023)	0.044

The length of CI (L) is computed as L= upper CI – lower CI.

TABLE (2): A CI of $\hat{\beta}_{CMG}$ and $\hat{\beta}_{CMG}$ in contaminated Panel

	$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$		$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$		$\hat{\beta}_{CMG}$		$\hat{\beta}_{RCMG}$	
	CI	L	CI	L	CI	L	CI	L	CI	L	CI	L
T/N	**20**				**30**				**50**			
					$\gamma_i = 0$							
20	(0.097,1.610)	1.513	(0.813,1.200)	0.387	(0.338,1.817)	1.479	(0.824,1.163)	0.339	(0.250,1.738)	1.488	(0.877,1.127)	0.250
30	(0.329,1.679)	1.345	(0.861,1.119)	0.258	(0.355,1.668)	1.314	(0.882,1.112)	0.230	(0.319,1.548)	1.229	(0.922,1.075)	0.153
50	(0.237,1.629)	1.392	(0.905,1.096)	0.191	(0.492,1.576)	1.084	(0.928,1.070)	0.141	(0.402,1.499)	1.097	(0.946,1.057)	0.111
100	(0.540,1.482)	0.941	(0.935,1.064)	0.129	(0.501,1.460)	0.959	(0.943,1.047)	0.105	(0.615,1.372)	0.757	(0.960,1.038)	0.078
200	(0.535,1.444)	0.910	(0.962,1.041)	0.079	(0.587,1.368)	0.781	(0.969,1.027)	0.058	(0.637,1.376)	0.740	(0.975,1.024)	0.049
					$\gamma_i \sim iidU(0.1,0.3)$							
20	(0.155,1.841)	1.686	(0.825,1.204)	0.379	(0.019,1.675)	1.656	(0.835,1.150)	0.315	(0.310,1.684)	1.374	(0.878,1.127)	0.250
30	(0.245,1.945)	1.705	(0.863,1.122)	0.259	(0.310,1.687)	1.377	(0.883,1.113)	0.230	(0.456,1.608)	1.152	(0.923,1.085)	0.162
50	(0.266,1.522)	1.256	(0.912,1.098)	0.186	(0.427,1.656)	1.230	(0.918,1.069)	0.151	(0.425,1.473)	1.048	(0.943,1.056)	0.113
100	(0.483,1.512)	1.029	(0.930,1.060)	0.130	(0.444,1.443)	0.999	(0.948,1.051)	0.102	(0.554,1.474)	0.920	(0.958,1.037)	0.079
200	(0.470,1.434)	0.965	(0.953,1.045)	0.092	(0.596,1.405)	0.805	(0.965,1.032)	0.067	(0.699,1.302)	0.603	(0.974,1.026)	0.052
					$\gamma_i \sim iidU(0.5,1.5)$							
20	(0.068,1.805)	1.737	(0.789,1.226)	0.438	(0.256,1.603)	1.831	(0.823,1.179)	0.356	(0.252,1.851)	1.599	(0.860,1.138)	0.278
30	(0.115,1.949)	1.834	(0.854,1.163)	0.309	(0.466,1.541)	1.391	(0.889,1.106)	0.217	(0.327,1.621)	1.294	(0.908,1.081)	0.173
50	(0.258,1.560)	1.302	(0.886,1.096)	0.210	(0.570,1.472)	1.223	(0.924,1.076)	0.152	(0.357,1.608)	1.251	(0.934,1.064)	0.129
100	(0.468,1.569)	1.101	(0.934,1.063)	0.129	(0.594,1.426)	1.100	(0.949,1.050)	0.101	(0.526,1.479)	0.954	(0.961,1.039)	0.078
200	(0.595,1.443)	0.848	(0.955,1.045)	0.090	(0.687,1.308)	0.835	(0.961,1.039)	0.078	(0.662,1.373)	0.711	(0.968,1.028)	0.060

The length of CI (L) is computed as L= upper CI – lower CI.

CONCLUSION

An alternative approach of the Pesaran estimation's procedure is proposed in order to limit the influence of outliers and leverage observations in panel model. The Generalized-M estimator is introduced in the model together with the modification of the variance covariance matrix which results in the robust version of Pesaran's procedure (RCMG). The behaviour of RCMG is derived and as such the confidence interval of the parameter estimates can be constructed. The finite of sample behaviour of the estimation procedures are examined and compared via simulation experiments. The proposed estimator provides comparable CI with CMG in uncontaminated panel; however yields better CI than CMG in contaminated panel. This is shown in 95% CI, where the values of $\hat{\beta}_{RCMG}$ are $\pm 10\%$ from β for large N and T. This concludes that RCMG provides better estimates with and without the presence of outliers in the panel.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the grant support **USIM/ERGS-FST-33-50312** from the Universiti Sains Islam Malaysia (USIM), Malaysia.

REFERENCES

1. J. Coakley, A.M. Fuertes and R.P. Smith, *A Principal Components Approach to Cross-Section Dependence in Panels*, Mimeo, Birkberk College, University of London, 2002.
2. J. Bai and S. Ng, *Econometrica,* **70**, 191-221 (2002).
3. P.C.B. Philips, and D. Sul, *Econometrics Journal*, **6**, 217-259 (2003).
4. H.R. Moon, and B. Perron, *Journal of Econometrics*, **122**, 81-126 (2004).
5. G. Kapetanios, and M.H. Pesaran, *Alternative Approaches to Estimation and Inference in Large Multifactor Panels: Small sample Results with an Application to Modeling of Asset Returns*, CESIFO Working Paper, 2004.
6. J. Coakley, A.M. Fuertes and R P. Smith, *Computational Statistics and Data Analysis*, **50**, 2361-2380 (2006).
7. M.H. Pesaran, *Econometrica*, **74**(4), 967-1012 (2006).
8. A. Noman, *Testing for PPP in the Mean-Group Panel Regression Framework: Further Evidence*, Munich Personal RePEc Archive (MPRA) Paper No. 7860, 2008.
9. J.H. Stock, and M.W. Watson, *Journal of Business and Economic Statistics*, **20**, 147-162 (2002).
10. S.C. Peters, A. Samarov and R.E. Welsc. *Computational Procedures for Bounded-Influence and Robust Regression (TROLL: BIF and BIFMOD).* Technical Report 30**,** Center for Computational Research in Economics and Management Science, Massachusetts Institute of Technology, Cambridge MA, 1982.
11. K.C. Hung, S. H. Cheung, W.S. Chan, and L.X. Zhang, *Journal of Forecasting*, **28** (5), 445-464 (2008).