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MISSPECIFIED HETEROGENEITY IN PANEL DATA MODELS

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Comments welcome

Misspecified Heterogeneity in Panel Data Models

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Abstract: In this paper we analyse systematically through Monte Carlo simulations the consequences of misspecified heterogeneity on the most popular linear panel data models. We also illustrate our findings, through the estimation of a well known investment demand model.

Key words: Panel data, Misspecification, Monte Carlo analysis, Heterogeneity, Error components model, Fixed effects model, Random coefficients model.

August 1995

Misspecified Heterogeneity in Panel Data Models

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1. Introduction

The use of panel data has become increasingly popular in econometrics over the last decade. This is mainly due to its large information content, that is to its heterogeneity. Several models and approaches are able to deal with the key features of these data sets (see *Mátyás and Sevestre* [1992]), but three formulations are dominating the literature: the Fixed Effects (FE), the Error Components (EC) and the Random Coefficients (RC) models.

The central question is how to formalize the heterogeneity of the data. When few restrictions (if any) are made about it, we may end up with models which look quite realistic because of the absence of restrictive assumptions, but probably lack explanatory power, are hardly estimable, and are useless for prediction and/or structural analysis. If more restrictions are made than are strictly necessary, the model is not able to explain the real data generating process and it can be considered useless as well. The structure imposed on the heterogeneity is, therefore, crucial from the viewpoint of any analysis.

The FE, EC and RC models are dominating the theory and practice of panel data modelling because they are considered to be parsimonious, reflect well the heterogeneity of the data and, therefore, produce reliable and realistic parameter estimates.

The above three models rarely formalize the heterogeneity of the data (and the data generating process) absolutely correctly and, as a consequence, frequently in practice misspecified models are used for estimation and inference. It is, therefore, of paramount importance to analyse the behaviour of these models when they are misspecified or when their specification is not fully correct.

There are surprisingly few studies on the effects of misspecification in panel data models. *Baltagi* [1986] analyses the EC heterogeneity versus the Kmenta–type structure and concludes that for samples with short time series the EC model should be preferred. *Baltagi* [1992] investigates the effects of under– or over–specifying the structure of an EC model. He shows that underspecification (omission of an error component) results in inconsistency of the variance component's estimators, while overspecification has not such a harmful effect. *Deschamps* [1991] demonstrates for the same model that misspecification of the error structure induces bias in the estimators of the structural coefficients' variances as well. *Van den Doel and Kiviet* [1991] point out the serious consequences of incorrectly omitting the lagged dependent variable from the right hand side of a EC or fixed effects model.

In this paper we analyse systematically through Monte Carlo simulations the consequences of misspecification of the FE, EC and RC models on their estimators, the testing procedures used to test for (individual) specific effects, and the information criteria used to select between these models. We also illustrate our findings, through the estimation of an investment demand model.

2. Framework of the Analysis

In order to simplify the analysis we assume that the heterogeneity of the data is purely individual and there is complete time homogeneity. Our core model then is

$$y_{it} = x_{it}'\beta + z_{it}'\alpha_i + z_{it}^{*'}\gamma_i + u_{it}\,,$$

where x_{it}, z_{it} and z_{it}^* are the non stochastic right hand side variables of the model with dimensions $(k \times 1)$, $(k_z \times 1)$ and $(k^* \times 1)$ respectively; β is a fixed parameter vector of dimension $(k \times 1)$; α_i is an individual specific parameter vector of dimension $(k_z \times 1)$; γ_i is a vector of individual specific random variables of dimension $(k^* \times 1)$ with zero expected value, variances σ_j^2 $j = 1, \ldots, k^*$, and u_{it} is a white noise. By imposing restrictions on this core model we can get back all the familiar panel models and even more formulations for the heterogeneity:

1. if $z_{it} = 0$ and $z_{it}^* = x_{it}$, the Swamy's random coefficient model;
2. if $z_{it} = 0$ and $z_{it}^* = e_{it}$, where e_{it} is a dummy vector with all elements equal to zero except one which equals one, the error components model;
3. if $z_{it} = 0$, the functional error components model;
4. if $z_{it}^* = 0$ and $z_{it} = e_{it}$, the fixed effects model;

5. if $z^*_{it} = 0$ and $x_{it} = x_{it}$, the cross sectional model;

6. if $z^*_{it} = 0$, the varying coefficients model;

7. if $z_{it} = 0$ and $z^*_{it} = 0$, the the absolute homogenous model.

The analysis focuses on the behaviour of the main estimators, tests for specific effects and model selection criteria when the data generating process (DGP) is the core model or processes 1–7 and the FE, EC or RC models are fitted.

For the Monte Carlo data generation we used the following model specification:

$$y_{it} = \beta_1 x^{(1)}_{it} + \beta_2 x^{(2)}_{it} + \alpha^{(1)}_i z^{(1)}_{it} + \alpha^{(2)}_i z^{(2)}_{it} + \gamma^{(1)}_i z^{*(1)}_{it} + \gamma^{(2)}_i z^{*(2)}_{it} + u_{it}$$

$$\begin{aligned}
x^{(j)}_{it} &= x^{(j)}_{it-1} + \varepsilon^{(j)}_{x,it} \quad j = 1,2 \\
z^{(j)}_{it} &= z^{(j)}_{it-1} + \varepsilon^{(j)}_{z,it} \quad j = 1,2 \\
z^{*(j)}_{it} &= z^{*(j)}_{it-1} + \varepsilon^{(j)}_{z*,it} \quad j = 1,2 \\
\varepsilon^{(j)}_{x,it} &= \varepsilon^{(j)}_{z,it} = \varepsilon^{(j)}_{z*,it} \sim \text{Uniform}\,[-0.5, 0.5] \\
u_{it} &\sim N(0,1) \quad \gamma_i \sim N(0, 0.5) \\
\beta_1 &= \beta_2 = \alpha^{(2)}_i = 0.5 \quad \text{and} \quad \alpha^{(1)}_i = i\,.
\end{aligned}$$

2.1 Estimators Involved in the Analysis

The Swamy's RC model has two basic formulations (*Hsiao* [1992]). The one proposed originally assumes that restrictions 1 apply to the core model and the disturbance term is heteroscedastic ($E(u^2_{it}) = \sigma^2_i$). In this case the GLS estimator of the model is

$$\begin{aligned}
\widehat{\beta}_{GLS} &= (X'\Omega^{-1}X)^{-1}(X\Omega^{-1}y) \\
&= (\sum_{i=1}^{N} X_i'\Omega_i^{-1}X_i)^{-1}(\sum_{i=1}^{N} X_i'\Omega_i^{-1}y_i) \\
&= \sum_{i=1}^{N} R_i \underline{\widetilde{\beta}}_i,
\end{aligned}$$

where

$$R_i = \left\{ \sum_{i=1}^{N} [\Delta + \sigma^2_i (X_i'X_i)^{-1}]^{-1} \right\}^{-1} [\Delta + \sigma^2_i (X_i'X_i)^{-1}]^{-1},$$

$$\widetilde{\beta}_i = (X_i'X_i)^{-1}X_i'y_i$$

Ω, the covariance matrix of the composite disturbance term $x_{it}^{*'}\gamma_i + u_{it}$, is block diagonal, and the ith diagonal block equals

$$\Omega_i = X_i \Delta X_i' + \sigma_i^2 I_T,$$

where

$$E(\gamma_i \gamma_j') = \begin{cases} \Delta & \text{if } i = j \\ 0 & \text{if } i \neq j. \end{cases}$$

For an operational FGLS estimator we can obtain unbiased estimators of σ_i and Δ as

$$\begin{aligned} \widehat{\sigma}_i^2 &= \frac{\widehat{u}_i'\widehat{u}_i}{T-K} \\ &= \frac{1}{T-K} y_i'[I - X_i(X_i'X_i)^{-1}X_i']y_i, \end{aligned}$$

$$\begin{aligned} \widehat{\Delta} =& \frac{1}{N-1}\sum_{i=1}^{N}\left(\underline{\widetilde{\beta}}_i - N^{-1}\sum_{i=1}^{N}\underline{\widetilde{\beta}}_i\right) \\ & \left(\underline{\widetilde{\beta}}_i - N^{-1}\sum_{i=1}^{N}\underline{\widetilde{\beta}}_i\right)' \underbrace{-\frac{1}{N}\sum_{i=1}^{N}\widehat{\sigma}_i^2(X_i'X_i)^{-1}}_{A}. \end{aligned} \tag{1}$$

We have to take into account that this estimator for Δ is not necessarily non–negative definite. In this case Swamy suggests to set $A = 0$. With homoscedasticity of the disturbance term (second formulation of the Swamy model)

$$\Omega_i = X_i \Delta X_i' + \sigma^2 I_T$$

and $\widehat{\sigma}^2 = \widehat{u}'\widehat{u}/NT - k$.

The ML estimator can be obtained by maximising the log–likelihood function which has two slightly different forms. For the homoscedastic model:

$$\begin{aligned} \log L_1 =& -\frac{NT}{2}\log 2\pi - \frac{n}{2}\sum_i \log|X_i\Delta X_i' + \sigma^2 I_T| \\ & - \frac{1}{2}\sum_i (y_i - X_i\beta)'(X_i\Delta X_i' + \sigma^2 I_T)^{-1}(y_i - X_i\beta). \end{aligned} \tag{2}$$

(This formula is given in *Swamy* [1971, p.111] making the $\sigma_{ii}^2 = \sigma^2$ substitution.) Restrictions $\sigma^2 > 0$ and Δ and $X_i \Delta X_i + \sigma^2 I_T$ positive definite are imposed. The second form given in *Swamy* [1971, p.112] is

$$\begin{aligned}\log L_2 = &-\frac{NT}{2}\log 2\pi - \frac{T-K}{2}\sum_i \log\sigma^2 - \frac{1}{2}\sum_i \log|X_i'X_i| \\ &-\frac{1}{2}\sum_i \log|\Delta + \sigma^2(X_i'X_i)| - \frac{T-K}{2}\sum_i \frac{\widehat{\sigma}_i}{\sigma^2} \\ &-\frac{1}{2}\sum_i (\widetilde{\beta}_i - \bar{\beta}')(\Delta + \sigma^2(X_i'X_i))^{-1}(\widetilde{\beta}_i - \bar{\beta}),\end{aligned} \tag{3}$$

with the same restriction as in $\log L_1$ except that now $\Delta + \sigma^2(X_i'X_i)^{-1}$ must be positive definite. For the heteroscedastic model $\log L_1$ and $\log L_2$ and the constraints are the same as for the homoscedastic model just σ^2 must be replaced by σ_i^2. To compute the ML estimator we use the GAUSS new Constrained ML (CML) module. It is possible to use this module not only to evaluate the log–likelihood but also the gradient, Hessian or Jacobian constraints which can speed up the iterations considerably.

We get the EC model by applying restrictions 2 to the core model. The GLS estimator for the model is then (*Mátyás* [1992])

$$\widehat{\beta}_{GLS} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y\,,$$

where the covariance matrix Ω has the structure

$$\Omega = \sigma^2(I_{NT} - (I_N \otimes \frac{J_T}{T})) + (\sigma^2 + T\sigma_\gamma^2)(I_N \otimes \frac{J_T}{T})$$

with σ^2 being the common variance of the white noise term u_{it} and σ_γ^2 the variance of the individual effects γ_i and I is the identity matrix of given size and J is the matrix of ones of given size. To use the FGLS estimator we need consistent estimators for the variance components:

$$\widehat{\sigma}^2 = \frac{\widehat{u}'(I_{NT} - (I_N \otimes \frac{J_T}{T}))\widehat{u}}{N(T-1)-K}, \quad \text{and}$$

$$\widehat{\sigma}_\gamma^2 = \frac{1}{NT-K}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{u}_{it}^2 - \widehat{\sigma}^2\,.$$

There are no serious problems with applying the ML estimator, but, as noted by *Breusch* [1987], the likelihood function is not globally concave, and therefore multiple local maxima may arise, and, also, implied estimates of the variance components may be negative. So we applied the Iterated GLS (IGLS) estimator (suggested by *Breusch* [1987]) as well. This represents an iterative procedure between $\widehat{\beta}$ obtained by GLS and the maximised concentrated log–likelihood, maximised over the variance components σ^2 and σ_γ^2 given β (CML). The series

$$\begin{pmatrix} \widehat{\sigma}^2 \\ \widehat{\sigma}_\gamma^2 \end{pmatrix}_{j,CML}, \quad \widehat{\beta}_{j,GLS}; \quad \begin{pmatrix} \widehat{\sigma}^2 \\ \widehat{\sigma}_\gamma^2 \end{pmatrix}_{j+1,CML}, \quad \widehat{\beta}_{j+1,GLS}; \quad \ldots$$

have quite good convergence properties.

The Within estimator for both the EC and FE models is

$$\widehat{\beta}_w = (X'(I_{NT} - (I_N \otimes \frac{J_T}{T}))X)^{-1}X'(I_{NT} - (I_N \otimes \frac{J_T}{T}))y\,.$$

2.2 Tests Involved in the Analysis

We are interested in testing for the presence of individual specific effects. For the EC model we analyse the behaviour of the variance decomposition (F), the one and two sided LM and the LR tests. The variance decomposition test (*Mátyás* [1992]) is based on the test statistic

$$F_1 = \frac{\widehat{u}'(I_N \otimes \frac{J_T}{T})\widehat{u}\,(N-k)^{-1}}{\widehat{u}'(I_{NT} - (I_N \otimes \frac{J_T}{T}))\widehat{u}\,[N(T-1)-k)]^{-1}}\,,$$

which is distributed as an $F\,(N-k,\ N(T-1)-k)$ random variable under $H_0 :, \sigma_\gamma^2 = 0$ where $\widehat{u}$ is the OLS residual from the model obtained by applying restrictions 2.

The *two sided LM* test (*Breusch and Pagan* [1980]) is based on the

$$LM2 = \left(\frac{NT}{2(T-1)}\right)\left(\frac{\widehat{u}'(I_N \otimes J_T)\widehat{u}}{\widehat{u}'\widehat{u}} - 1\right)^2$$

test statistic which under H_0 is asymptotically distributed as a $\mathcal{X}^2$ random variable with 1 degree of freedom.

The *one sided LM* test (*Baltagi et al.* [1992], *Moulton and Randolph* [1989], and *Honda* [1985]) is based on the

$$LM1 = \left(\frac{NT}{2(T-1)}\right)^{\frac{1}{2}}\left(\frac{\widehat{u}'(I_N \otimes J_T)\widehat{u}}{\widehat{u}'\widehat{u}} - 1\right)$$

test statistic which under the null hypothesis $H_0 : \sigma_\mu^2 = 0$ (against the alternative hypothesis $H_A : \sigma_\mu^2 > 0$) has standard normal asymptotic distribution if N & $T \to \infty$.

The one sided *LR* test (*Baltagi et al.* [1992]) is based on the test statistic

$$LR = -2 \log \frac{\text{likelihood(restricted)}}{\text{likelihood(unrestricted)}}$$

which is asymptotically (N & $T \to \infty$) distributed as $1/2\mathcal{X}^2(0) + 1/2\mathcal{X}^2(1)$ random variable (*Gourieroux, Holly and Monfort* [1982] and *Gourieroux and Monfort* [1989]). To compute the test we used two methods: the true ML for the constrained and unconstrained model (*Hsiao* [1986]) and the iterative procedure proposed by *Oberhofer and Kmenta* [1974].

For the heteroscedastic RC model (*Hsiao* [1986], *Swamy* [1970], [1971]) the statistic

$$f^* = \sum_{i=1}^{N} \frac{(\widehat{\beta}_{i,ols} - \widetilde{\beta}^*)' X_i' X_i (\widehat{\beta}_{i,ols} - \widetilde{\beta}^*)}{\widehat{\sigma}_i^2}$$

can be used to test $H_0 : \ \beta_1 = \ldots, \beta_k = \beta$, where

$$\widetilde{\beta}^* = (\sum_{i=1}^{N} \frac{1}{\widehat{\sigma}_i^2} X_i' X_i)^{-1} (\sum_{i=1}^{N} \frac{1}{\widehat{\sigma}_i^2} X_i' y_i).$$

This has a $\mathcal{X}^2(k(N-1))$ distribution under the null hypothesis. The same test can be used when the FE model (with heteroscedasticity) is under investigation, because the test is valid regardless the alternative hypothesis. To take explicitly into account the randomness assumption of the coefficients, a test based on $H_0 : \ \Delta = 0$ can be used.

For the homoscedastic RC model the statistic (*Hsiao* [1986])

$$F_2 = \frac{(\widehat{u}_7' \widehat{u}_7 - \widehat{u}^{*\prime} \widehat{u}^*)/(N-1)k}{(\widehat{u}^{*\prime} \widehat{u}^*)/N(T-k)}$$

can be used, which has an $F((N-1)(k-1), N(T-k)$ distribution under the null hypothesis, and where $\widehat{u}^*$ is the vector of piled up residuals formed from the individual OLS residuals (OLS performed separately on the individual time series).

As shown by *Hsiao* [1986], the two sided LM test (Breusch and Pagan test) can be adapted to the Swamy type model, because introducing random coefficient variation gives to the dependent variable of the ith individual a different variance. Using the formulation

$$\frac{\overline{y}_i}{\sigma_i} = \frac{1}{\sigma_i} \overline{x}_i' \beta + \omega_i \,, \quad i = 1, \ldots, N$$

and replacing σ_i by its estimate $\widehat{\sigma}_i = \sqrt{\widehat{u}_i'\widehat{u}_i/(T-l)}$, the model

$$(T\widehat{\omega}_i^2 - 1) = \frac{1}{\widehat{\sigma}_i^2}\left(\sum_{j=1}^{k}\sum_{j'=1}^{k} \overline{x}_{ji}\overline{x}_{j'i}\sigma^2_{\alpha jj'} + \eta_i\right)$$

is estimated by OLS, where $\widehat{\omega}$ is the OLS residual from the previous formulation. When $N \to \infty$ and $T \to \infty$ the one half predicted sum of squares of the regression, that is the LM statistic,

$$LM3 = \frac{\sum_i \widehat{(t\omega_i^2 - 1)}^2}{2}$$

has a χ^2 distribution with $k(k+1)/2$ degrees of freedom under the null hypothesis $H_0 : \Delta = 0$.

For the FE model the null hypothesis of homogeneity of the individual specific constant term(s) can be tested (*Balestra* [1992]) with the statistic

$$F_3 = \frac{(\widehat{u}_7'\widehat{u}_7 - \widehat{u}_4'\widehat{u}_4)/N}{(\widehat{u}_4'\widehat{u}_4)/N(T-1) - k}$$

which has an $F(N, N(T-1)-k)$ distribution under the null hypothesis, and where $\widehat{u}_j$, $j = 4, 7$ are the OLS residuals from models 4 and 7.

We also use the Hausman test to test the specification of the models FE against EC (HM1), and Homegenous against EC (HM2), and the White test to test for homoscedasticity given that models 1–3 and 5–6 can be considered as a form of heteroscedasticity (and serial correlation). To compute the White test we regress the OLS residuals on $(1, x_1, x_2, x_1^2, x_2^2, x_1x_2)$ and use the test statistic NTR^2, where R^2 is the coefficient of determination of this regression. It has a $\chi^2(k)$ distribution, where k is the number of variables in the model.

Summing up we study the following estimators:

Analysed Estimators

Fitted model	Estimators
RC	FGLS*, OLS, ML*
EC	FGLS, OLS, Within, ML, IGLS
FE	Within

* For the homoscedastic and the heteroscedastic models as well.

and the following tests:

Analysed Tests

Fitted model	Tests
RC	Swamy's f^*, two sided LM, F_2, White
EC	F_1, one and two sided LM, LR, White, Hausman
FE	F_3, Swamy's f^*, two sided LM, Hausman

The usefullness of the Bayesian (BIC) and Akaike (AIC) information criteria in selecting the correct model is also analysed. Overall, the behaviour of nine estimators and ten testing procedures is under investigation for each data generating process, and the Hausman test for two pairs of specifications.

3. Simulation Results

3.1 Estimators

Results on the different estimation procedures for the mean bias and mean squared errors of β can be found in Tables 1–4 for a range of different sample sizes. It is fairly clear that the main decision one has to make about the heterogeneity is whether it is observed or not. Getting wrong the specification at this stage will certainly cause biases in the estimated parameters. On the other hand, while for the fixed effects heterogeneity the given form of the specification matters, for the latent (or residual) individual heterogeneity its form (whether an error components or a random coefficients approach was used) does not matter too much. The IGLS–EC, ML–EC and FGLS–EC estimators are quite robust against the RC model and vice versa. The ML–RCM and FGLS–RCM were robust against an error components model, especially when N is large.

The really interesting issue is that the fixed effects model behaves, from the point of view of the estimation, very much like an EC model. As a result the IGLS–EC, ML–EC and FGLS–EC estimators are very robust against a fixed effects specification (even in small samples). This means that these estimators provide good point estimates regardless of whether the real DGP has an error components, random coefficients or fixed effects structure. And these results hold not only in terms of bias but in terms of mean squared errors as well.

The Within estimator has a rock solid behaviour as well. It is robust against all specifications considered except for the functional fixed effects and the cross sectional DGP, which is quite natural.

A further outcome of this experiment is that in small samples (especially if N is small) anything can happen. For example, estimators may have some bias where, theoretically, they are not supposed to have, etc.

It is interesting to compare the behaviour of the FGLS and ML estimators for the RCM models, especially because the ML estimators have never been used in practice so far to estimate and RCM model due to the heavy computing involved. It can be seen from Tables 1–4 that the estimation results for the simulated data sets are pretty close to each other for all FGLS and ML estimators involved in the analysis. The L_1 and L_2 ML estimators (see (2) and (3)) led, as expected, to numerically identical results. All this would suggest the use of the much more simple to perform FGLS estimators intead of the theoretically (asymptotically) optimal but extremely hard to compute ML estimators. There is, however, an important difference between these estimators. While the FGLS estimators truncate to zero ($A = 0$) if the positivity constraints (1) (about $\widehat{\Delta}$) are not satisfied, the LM estimators take always into account these constraints. These were effective in about 60%–70% of the cases, which means that on the average the truncation required by the FGLS does not have any severe effects. This does not mean, however, that the truncation cannot have (even serious) effects for some data sets. This is well reflected by the estimation results on the Grunfeld data (see Table 13) where truncation was necessary for both the homo- and heteroscedastic FGLS. In this case, there is a non–negligible difference between the FGLS and ML parameter estimates which means that one should rely on the ML rather the FGLS estimates. This means that we suggest to use the FGLS estimator as far as the $A = 0$ truncation is not necessary, but otherwise the use of the ML is recommended.

3.2 Testing Procedures

The main results are summarised in Tables 5–8. Columns 1–5 and 8 and rows 1–6 and 8 show the power of the tests under different alternative hypotheses, while row 7 shows the empirical size (theoretical 5%) of the tests. Columns 6, 7 and 9 row 1 show the power of the RCM tests against the correct alternative hypothesis and rows 2–6 and 8 show the power robustness of the RCM tests against misspecification.

The results are impressive. All the analysed tests, except the f^*, F_2 and White's, have excellent power and size behaviour for all the sample sizes, and only the size of the LM/RCM test seems to be of concern. On the other hand it is difficult to understand the poor size behaviour of the f^* and the F_2 tests. The only plausible explanation we could find is that for the individial regressions the sum of squared residuals may be frequently unusually low inflating up the value of the test statistic, forcing the test to always reject.

These results suggest that the F_1, F_3, one and two sided LM and the LR test can be used quite efficiently to test for individual heterogeneity, without worrying too much about the specification of the model.

The HM1 and HM2 Hausman test results are missbehaved, which follows from the setup of the experiments. HM1 always accepts the null, while HM2 rejects the null for DGP 4 in over 90% of the cases and in less than 10% of the cases for all other DGP's, regardless the sample size.

The AIC and BIC model selection criteria (Tables 9–12) are performing surprisingly well. We have to consider two cases: a) when amongst the GDP's we analyse (which is assumed model: FE, EC, RCM, Homo.) the true DGP can be found and b) when the true DGP can be represented by a model not taken into account. In case a) the BIC criteria will almost certainly pick up the correct model, especially if the sample is large in N, while the AIC fails only in the case of the FE model due to the improper penalty it is using for the number of parameters. For small N the BIC has a uniformly better behaviour than the AIC. Based in these results we can say that these information criteria are working very efficiently in choosing the correct model and in practice we should rely on them much more frequently. In case b), however, we are in trouble, which is natural because the correct model is not taken in account and this results in the erratic behaviour of these criteria.

3.3 Discussion

During the simulations we found several problems:

- With DGP7 (completely homogenous data):
  - For the IGLS estimator in more than 50% of the cases, regardless the sample size, the estimated variance ratio ($\frac{\sigma^2}{\sigma^2+T\sigma_\gamma^2} = \theta$) is larger than 1. In this case we force $\widehat{\theta} = 1$.

- For the FGLS–EC estimator in about 50% of the cases the estimated variance ratio is negative. Then we use alternative estimators to obtain an estimate for the individual specific variance (*Greene* [1992]).

- In many cases, particularly with DGP5 and DGP7, for both the homo– and heteroscedastic FGLS–RCM estimators, the estimate of Δ is negative–definite. Then we use the solution proposed by *Swamy* [1970], which consist of dropping the term $\frac{1}{N}\sum_{i=1}^{N}\hat{\sigma}_i^2(X_i, X_i)^{-1}$ $(A = 0)$.
- We also have some convergence problems with the ML estimators.

The most important numerical problems are summarised in Table 16.

It is well known that all the above problems may theoretically happen. But, while theoreticians frequently argue that only in unlikely special cases, our study showed that this is quite often a real nuisance.

4. An Application

To illustrate our findings we estimated a classical model for investment demand based on Grunfeld's well known data set (*Grunfeld* [1958], *Grunfeld and Griliches* [1960]), which has been used several times (*Boot and deWitt* [1960], *Swamy* [1970], *Maddala* [1981] *Baltagi et al.* [1992], *Greene* [1993, 445–446.], etc.) to investigate the behaviour econometric methods in a panel data context.

The model

$$I_{it} = \beta_1 + \beta_2 F_{it} + \beta_3 C_{it} + u_{it}$$

is estimated, where I_{it} is the gross investment of firm i at period t, F_{it} is the market value of firm i at the end of the previous year (end $t-1$), C_{it} is the value of the stock of plant and equipment of firm i at the end of the previous year (end $t-1$), firms i are mayor US companies ($i = 1, \ldots, 10$) and the time series run from 1935 to 1954 ($t = 1, \ldots, 20$). The explanatory variables in the model stand for the anticipated profit and the expected replacement investment required.

The estimation results are summarised in Tables 13–15. It can be seen, as predicted by the simulation analysis, the estimated values of the structural parameters of the model produced by the different estimators are quite close to each other.[1] All the different hypothesis testing procedures reject the null hypothesis of homogeneity at 5% and 1% significance levels. Both the AIC and BIC criteria pick up the RCM/hetero model as the true model generating the data.

In the light of these results we think it is legitimate to ask the question whether we have enough information in the data and appropriate tools (except for the information criteria) to make confidently a choice between the RC, EC and FE models for a given data set. Although these models are by no means observationally equivalent, the choice between them, in today's practice, seems to be much more based on subjective judgement, than real information extracted from the data. This is not necessarily bad, but we should be aware of it.

4. Conclusion

In this paper we analyse the consequences of misspecification of the Fixed Effects, Error Components and Random Coefficients models on their estimators, the testing procedures used to test for (individual) specific effects, and the information criteria used to select between these models. We also illustrate our findings, through the estimation a well known investment demand model. We suggest that the structure of these models and the lack of power of our testing procedures against these models may not enable us to make a clear cut decision when picking up a specification for practical purposes. We also suggest that this may not matter too much after all, given that we probably end up with very similar parameter estimates whatever model we choose.

Computer programs: The Gauss computer codes used for this paper are available on the World Wide Web :\\www.monash.edu.au/econometrics/workpaps.htm.

[1] The Between estimator has no practical importance, and was not analysed in the simulation study.

Table 1a: Mean bias for β_1
$N = 25, T = 10$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.1466	0.1794	0.1429	0.1429	0.1429
2. EC	0.1605	0.1388	0.1186	0.1188	0.1185
3. Func. E.C	0.1218	0.1578	0.1185	0.1186	0.1186
4. FE	3.2144	0.1388	0.1389	0.1407	0.1389
5. Cross Sect.	12.9768	12.9941	12.9893	12.9891	12.9896
6. Func. F.E.	2.0037	1.5492	1.5401	1.5415	1.5411
7. Homogen.	0.0762	0.1388	0.0771	0.0769	0.0768
8. Complete	2.0070	1.5512	1.5426	1.5441	1.5436

Table 1a: Mean bias for β_1 (continued)
$N = 25, T = 10$

DGP	FGLS–RCM/hom	FGLS–RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.1388	0.1440	0.1295	0.1409
2. EC	0.1648	0.1668	0.1732	0.1755
3. Func. E.C	0.1356	0.1392	0.1199	0.1306
4. FE	2.8772	2.4721	2.7895	2.4221
5. Cross Sect.	12.9933	13.0042	13.021	13.019
6. Func. F.E.	1.8811	1.5395	1.7814	1.3713
7. Homogen.	0.1054	0.1127	0.0893	0.1044
8. Complete	1.8837	1.5396	1.7806	1.3684

Table 1b: Mean squared errors for β_1
$N = 25, T = 10$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0371	0.0.0466	0.0337	0.0338	0.0337
2. EC	0.0431	0.0306	0.0237	0.0238	0.0237
3. Func. E.C	0.0216	0.0381	0.0203	0.0203	0.0203
4. FE	15.651	0.0306	0.0305	0.0309	0.0305
5. Cross Sect.	171.53	170.15	170.23	170.20	170.21
6. Func. F.E.	6.4299	3.9496	3.9095	3.9080	3.9064
7. Homogen.	0.0094	0.0306	0.0094	0.0094	0.0094
8. Complete	6.4210	3.9510	3.9080	3.9070	3.9050

Table 1b: Mean squared errors for β_1 (continued)
$N = 25, T = 10$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0293	0.0322	0.0276	0.0326
2. EC	0.0506	0.0523	0.0470	0.0480
3. Func. E.C	0.0288	0.0315	0.0236	0.0278
4. FE	13.023	9.6730	12.601	9.3391
5. Cross Sect.	169.62	169.34	169.42	169.37
6. Func. F.E.	5.0808	3.3592	4.8477	2.9046
7. Homogen.	0.0195	0.0221	0.0133	0.0175
8. Complete	5.0830	3.3640	4.8550	2.9110

Table 2a: Mean bias for β_1

$N = 25$, $T = 25$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.1350	0.1240	0.1217	0.1216	0.1216
2. EC	0.0958	0.0553	0.0523	0.0523	0.0522
3. Func. E.C	0.0997	0.0905	0.0860	0.0859	0.0859
4. FE	1.9968	0.0553	0.0552	0.0552	0.0552
5. Cross Sect.	13.0411	13.0033	13.0055	13.0053	13.0051
6. Func. F.E.	1.8982	1.5185	1.5067	1.5069	1.5071
7. Homogen.	0.0317	0.0553	0.0320	0.0319	0.0319
8. Complete	1.9010	1.5198	1.5084	1.5087	1.5087

Table 2a: Mean bias for β_1 (continued)

$N = 25$, $T = 25$

DGP	FGLS–RCM/hom	FGLS–RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0978	0.0965	0.0958	0.0966
2. EC	0.0953	0.0926	0.0937	0.0908
3. Func. E.C	0.0950	0.0919	0.0940	0.0886
4. FE	1.7814	1.6207	1.7586	1.6265
5. Cross Sect.	12.9969	13.0015	12.983	12.985
6. Func. F.E.	1.6960	1.4886	1.7774	1.5189
7. Homogen.	0.0439	0.0451	0.0369	0.0373
8. Complete	1.7016	1.4935	1.7776	1.5219

Table 2b: Mean squared errors for β_1
$N = 25$, $T = 25$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0283	0.0248	0.0238	0.0238	0.0238
2. EC	0.0136	0.0046	0.0040	0.0040	0.0040
3. Func. E.C	0.0140	0.0121	0.0109	0.0108	0.0108
4. FE	5.8698	0.0046	0.0046	0.0047	0.0046
5. Cross Sect.	170.55	170.21	170.17	170.16	170.17
6. Func. F.E.	6.3956	3.6631	3.6557	3.6552	3.6550
7. Homogen.	0.0014	0.0046	0.0014	0.0014	0.0014
8. Complete	6.4298	3.6782	3.6716	3.6713	3.6715

Table 2b: Mean squared errors for β_1 (continued)
$N = 25$, $T = 25$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0151	0.0147	0.0145	0.0154
2. EC	0.0142	0.0131	0.0140	0.0131
3. Func. E.C	0.0144	0.0136	0.0142	0.0127
4. FE	4.7390	4.0855	4.6778	3.9991
5. Cross Sect.	168.76	168.84	168.75	168.80
6. Func. F.E.	5.3213	4.0590	5.0918	3.6919
7. Homogen.	0.0029	0.0030	0.0022	0.0023
8. Complete	5.3453	4.0635	5.0945	3.7013

Table 3a: Mean bias for β_1
$N = 100, T = 10$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0791	0.0890	0.0760	0.0760	0.0760
2. EC	0.0784	0.0695	0.0598	0.0599	0.0598
3. Func. E.C	0.0632	0.0816	0.0621	0.0621	0.0621
4. FE	5.9392	0.0695	0.0695	0.0695	0.0605
5. Cross Sect.	50.4295	50.4722	50.4663	50.4660	5046.61
6. Func. F.E.	3.8018	2.9605	2.9607	2.9513	2.9611
7. Homogen.	0.0377	0.0695	0.0378	0.0377	0.0377
8. Complete	3.7985	2.9588	2.9584	2.9590	2.9588

Table 3a: Mean bias for β_1 (continued)
$N = 100, T = 10$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0692	0.0715	0.0636	0.0688
2. EC	0.0831	0.0829	0.0812	0.0794
3. Func. E.C	0.0704	0.0714	0.0632	0.0651
4. FE	5.6642	4.8578	5.3979	4.7277
5. Cross Sect.	50.4629	50.5007	50.4524	50.4459
6. Func. F.E.	3.5079	2.7862	3.4406	2.7581
7. Homogen.	0.0548	0.0583	0.0379	0.0490
8. Complete	3.5043	2.7833	3.4422	2.7730

Table 3b: Mean squared errors for β_1
$N = 100, T = 10$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0088	0.0099	0.0077	0.0078	0.0077
2. EC	0.0102	0.0065	0.0050	0.0050	0.0050
3. Func. E.C	0.0057	0.0097	0.0054	0.0053	0.0053
4. FE	56.145	0.0065	0.0066	0.0066	0.0066
5. Cross Sect.	2580.78	2559.31	2161.99	2562.06	2561.98
6. Func. F.E.	20.898	19.574	13.016	13.017	13.018
7. Homogen.	0.0020	0.0065	0.0020	0.0020	0.0020
8. Complete	20.887	13.572	13.017	13.017	13.019

Table 3b: Mean mean squared errors for β_1 (continued)
$N = 100, T = 10$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0069	0.0766	0.0062	0.0072
2. EC	0.0114	0.0101	0.0103	0.0101
3. Func. E.C	0.0079	0.0078	0.0062	0.0066
4. FE	48.189	34.580	45.445	34.793
5. Cross Sect.	2550.24	2547.34	2548.05	2547.34
6. Func. F.E.	18.457	11.971	18.375	12.117
7. Homogen.	0.0042	0.0046	0.0022	0.0038
8. Complete	18.504	12.007	18.423	12.157

Table 4a: Mean bias for β_1
$N = 100, T = 25$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0684	0.0629	0.0615	0.0615	0.0615
2. EC	0.0452	0.0274	0.0255	0.0255	0.0255
3. Func. E.C	0.0489	0.0467	0.0440	0.0440	0.0440
4. FE	3.7011	0.0274	0.0274	0.0274	0.0274
5. Cross Sect.	50.4130	50.5243	50.5176	50.5178	50.510
6. Func. F.E.	3.7716	2.9332	2.9288	2.9287	2.9262
7. Homogen.	0.0151	0.0274	0.0155	0.0155	0.0155
8. Complete	3.7713	2.9350	2.9302	2.9301	2.9267

Table 4a: Mean bias for β_1 (continued)
$N = 100, T = 25$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0501	0.0491	0.0597	0.0706
2. EC	0.0461	0.0454	0.0573	0.0586
3. Func. E.C	0.0492	0.0476	0.0575	0.0642
4. FE	3.3790	3.0965	3.3882	3.0784
5. Cross Sect.	50.4867	50.5002	52.021	52.014
6. Func. F.E.	3.3796	2.9625	2.6930	2.7890
7. Homogen.	0.0218	0.0224	0.0193	0.0212
8. Complete	3.3774	2.9609	3.3212	3.0083

Table 4b: Mean squared errors for β_1
$N = 100, T = 25$

DGP	OLS	Within	FGLS–EC	IGLS–EC	ML–EC
1. Swamy	0.0090	0.0079	0.0071	0.0071	0.0071
2. EC	0.0041	0.0011	0.0010	0.0010	0.0010
3. Func. E.C	0.0054	0.0034	0.0034	0.0034	0.0034
4. FE	25.911	0.0011	0.0011	0.0011	0.0011
5. Cross Sect.	3123.47	3139.25	3137.81	3137.82	3137.82
6. Func. F.E.	26.527	15.926	15.801	15.803	15.803
7. Homogen.	0.0011	0.0011	0.0004	0.0004	0.0004
8. Complete	26.496	15.962	15.835	15.837	15.837

Table 4b: Mean squared errors for β_1 (continued)
$N = 100, T = 25$

DGP	FGLS–RCM/hom	FGLS-RCM/het	ML–RCM/hom	ML–RCM/het
1. Swamy	0.0048	0.0045	0.0046	0.0063
2. EC	0.0042	0.0040	0.0042	0.0045
3. Func. E.C	0.0046	0.0040	0.0045	0.0058
4. FE	23.368	20.100	23.374	20.110
5. Cross Sect.	3133.01	3131.80	3132.56	3131.80
6. Func. F.E.	25.233	18.640	24.757	18.656
7. Homogen.	0.0008	0.0009	0.0005	0.0005
8. Complete	25.262	18.669	24.811	18.686

Table 5: Number of rejections of H_0

$N = 25, T = 10$

DGP	F1	LM2	LM1	LR/igls	LR	f^*	F2	F3	LM3	White
1. Swamy	829	761	818	837	781	977	1000	827	909	429
2. EC	1000	1000	1000	1000	993	996	1000	1000	982	103
3. Func. E.C	840	777	831	857	810	909	996	840	753	134
4. FE	1000	1000	1000	1000	1000	1000	1000	1000	1000	948
5. Cross Sect.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
6. Func. F.E.	1000	1000	1000	1000	1000	1000	1000	1000	1000	715
7. Homogen.	45	42	39	68	30	385	795	44	197	56
8. Complete	1000	1000	1000	1000	1000	1000	1000	1000	998	716

Table 6: Number of rejections of H_0

$N = 25, T = 25$

DGP	F1	LM2	LM1	LR/igls	LR	f^*	F2	F3	LM3	White
1. Swamy	1000	1000	1000	1000	1000	1000	1000	1000	1000	918
2. EC	1000	1000	1000	1000	1000	1000	1000	1000	1000	292
3. Func. E.C	1000	1000	1000	1000	1000	1000	1000	1000	994	505
4. FE	1000	1000	1000	1000	1000	1000	1000	1000	1000	998
5. Cross Sect.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
6. Func. F.E.	1000	1000	1000	1000	1000	1000	1000	1000	1000	930
7. Homogen.	50	40	44	79	32	138	836	47	70	59
8. Complete	1000	1000	1000	1000	1000	1000	1000	1000	1000	934

Table 7: Number of rejections of H_0
$N = 100, T = 10$

DGP	F1	LM2	LM1	LR/igls	LR	f^*	F2	F3	LM3	White
1. Swamy	999	999	999	999	999	1000	1000	999	1000	264
2. EC	1000	1000	1000	1000	1000	1000	1000	1000	1000	46
3. Func. E.C	1000	999	1000	1000	1000	1000	1000	1000	995	72
4. FE	1000	1000	1000	1000	1000	1000	1000	1000	1000	285
5. Cross Sect.	1000	1000	1000	1000	1000	1000	1000	1000	1000	300
6. Func. F.E.	1000	1000	1000	1000	1000	1000	1000	1000	1000	256
7. Homogen.	43	36	40	73	34	791	999	45	550	14
8. Complete	1000	1000	1000	1000	1000	1000	1000	1000	1000	257

Table 8: Number of rejections of H_0
$N = 100, T = 25$

DGP	F1	LM2	LM1	LR/igls	LR	f^*	F2	F3	LM3	White
1. Swamy	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
2. EC	1000	1000	1000	1000	1000	1000	1000	1000	1000	389
3. Func. E.C	1000	1000	1000	1000	1000	1000	1000	1000	1000	767
4. FE	1000	1000	1000	1000	1000	1000	1000	1000	1000	990
5. Cross Sect.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
6. Func. F.E.	1000	1000	1000	1000	1000	1000	1000	1000	1000	984
7. Homogen.	57	47	53	101	48	246	1000	56	158	52
8. Complete	1000	1000	1000	1000	1000	1000	1000	1000	1000	984

Table 9: The AIC and BIC criteria

$N = 25$, $T = 10$

The number of times a model chosen using AIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	79	168	100	646	7
2. EC	2	995	3	0	0
3. Func. E.C	131	419	308	135	7
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	892	108
6. Func. F.E.	0	79	0	0	921
7. Homogen.	945	1	48	6	0
8. Complete	0	83	0	0	917

The number of times a model chosen using BIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	324	0	298	378	0
2. EC	2	0	998	0	0
3. Func. E.C	339	0	625	36	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	939	61
6. Func. F.E.	0	0	206	63	675
7. Homogen.	995	0	4	1	0
8. Complete	0	0	267	66	667

One column represents an assumed DGP and defines the likelihood chosen.
One row adds up to 1000.

Table 10: The AIC and BIC criteria

$N = 25, T = 25$

The number of times a model chosen using AIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	23	0	976	1
2. EC	0	1000	0	0	0
3. Func. E.C	0	915	1	75	9
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	37	963
6. Func. F.E.	0	0	0	0	1000
7. Homogen.	962	0	35	2	1
8. Complete	0	0	0	0	1000

The number of times a model chosen using BIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	0	4	996	0
2. EC	0	0	1000	0	0
3. Func. E.C	1	0	783	216	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	53	947
6. Func. F.E.	0	0	1	0	999
7. Homogen.	997	0	3	0	0
8. Complete	0	0	1	0	999

One column represents an assumed DGP and defines the likelihood chosen.
One row adds up to 1000.

Table 11: The AIC and BIC criteria

$N = 100, T = 10$

The number of times a model chosen using AIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	17	7	976	0
2. EC	0	1000	0	0	0
3. Func. E.C	0	380	433	187	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	1000	0
6. Func. F.E.	0	0	0	0	1000
7. Homogen.	856	0	37	107	0
8. Complete	0	0	0	0	1000

The number of times a model chosen using BIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	0	30	970	0
2. EC	0	0	1000	0	0
3. Func. E.C	3	0	932	65	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	1000	0
6. Func. F.E.	0	0	83	0	917
7. Homogen.	886	0	10	104	0
8. Complete	0	0	83	0	917

One column represents an assumed DGP and defines the likelihood chosen.
One row adds up to 1000.

Table 12: The AIC and BIC criteria

$N = 100, T = 25$

The number of times a model chosen using AIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	0	0	1000	0
2. EC	0	1000	0	0	0
3. Func. E.C	0	995	0	5	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	1000	0
6. Func. F.E.	0	47	0	10	943
7. Homogen.	891	0	62	47	0
8. Complete	0	47	0	10	943

The number of times a model chosen using BIC

DGP	Homogen. (7)	FE (4)	EC (2)	RCM/homo (1)	RCM/het
1. Swamy	0	0	0	1000	0
2. EC	0	0	1000	0	0
3. Func. E.C	0	0	808	192	0
4. FE	0	1000	0	0	0
5. Cross Sect.	0	0	0	1000	0
6. Func. F.E.	0	0	41	16	943
7. Homogen.	969	0	5	26	0
8. Complete	0	0	41	16	943

One column represents an assumed DGP and defines the likelihood chosen.
One row adds up to 1000.

Table 13: Estimation results on Grunfeld's data
$N = 10$, $T = 20$

Estimator	OLS	Between	Within	FGLS–EC	IGLS–EC
β_1	-43.024 (9.498)	-9.103 (47.54)		-57.869 (28.81)	-57.805 (27.83)
β_2	0.115 (0.0058)	0.134 (0.0288)	0.109 (0.0119)	0.109 (0.0105)	0.109 (0.0104)
β_3	0.231 (0.0255)	0.035 (0.1911)	0.310 (0.0174)	0.308 (0.0172)	0.308 (0.0172)

Table 13: Estimation results on Grunfeld's data (continued)
$N = 10$, $T = 20$

Estimator	FGLS–RCM/het	FGLS–RCM	ML–EC	ML–RCM/het	ML–RCM
β_1	-9.530 (17.148)	-22.32 (23.61)	-57.806 (27.62)	-2.406 (5.814)	-22.330 (na)
β_2	0.081 (0.0187)	0.097 (0.0286)	0.109 (0.0103)	0.065 (0.018)	0.081 (0.016)
β_3	0.203 (0.053)	0.202 (0.070)	0.309 (0.017)	0.224 (0.051)	0.219 (0.027)
Log L			-1095.1	-844.6	-1130.3

Table 14: Hypothesis testing for Grunfeld's data
$N = 10, T = 20$

Test	F1	LM2	LM1	LR*	f^*
Calc. value	51.63	797.72	28.24	192.65	907.04
Distr.	F(7,187)	$\chi^2(1)$	$N(0,1)$	$1/2\chi^2(0) + 1/2\chi^2(1)$	$\chi^2(27)$

All tests reject the null hypothesis at 5% significance level.
Results for the LR and LR/igls tests are identical.

Table 14: Hypothesis testing for Grunfeld's data (continued)
$N = 10, T = 20$

Test	F2	F3	LM3	White
Calc. value	37.73	43.89	36785	91.36
Distr.	F(20, 170)	F(10, 187)	$\chi^2(6)$	$\chi^2(5)$

All tests reject the null hypothesis at 5% significance level.

Table 15: AIC and BIC results for Grunfeld's data
$N = 10, T = 20$

Model	AIC	BIC
Homogen.	-1195.4	-1202.0
FE	-1083.6	-1105.1
EC	-1100.1	1108.3
RCM/homo	-1140.3	1156.8
RCM/hetero	-847.5	-894.9

AIC = max $\sum_i \log L_i - k$ and BIC = max $\sum_i \log L_i - k/2 \log NT$.
The RCM/hetero model is selected by both AIC and BIC.

Table 15: **Numerical problems during the simulations**

$N = 25, T = 10$

DGP	FGLS–EC	$\widehat{\Delta}$/hom	$\widehat{\Delta}$/het	ML/hom	ML/het	Grad
1. Swamy	18	860	669	322	255	31
2. EC	0	820	577	260	258	18
3. Func. E.C	14	845	702	571	388	44
4. FE	0	677	31	106	26	0
5. Cross Sect.	0	1000	612	657	463	2
6. Func. F.E.	0	787	89	57	72	3
7. Homogen.	528	873	855	961	461	61
8. Complete	0	789	89	58	79	2

$N = 100, T = 10$

DGP	FGLS–EC	$\widehat{\Delta}$/hom	$\widehat{\Delta}$/het	ML/hom	ML/het	Grad
1. Swamy	0	836	356	0	0	596
2. EC	0	689	200	3	0	636
3. Func. E.C	0	823	493	17	3	613
4. FE	0	383	0	0	0	766
5. Cross Sect.	0	1000	556	180	40	286
6. Func. F.E.	0	583	3	0	0	743
7. Homogen.	549	882	836	263	23	845
8. Complete	0	856	3	0	0	703

FGLS-EC: number of times $\theta < 0$ for the FGLS–EC estimator.

$\widehat{\Delta}$/hom: number of times $\widehat{\Delta}$/homo is neg. def. for the FGLS/homo estimator.

$\widehat{\Delta}$/het: number of times $\widehat{\Delta}$/heter is neg. def. for the FGLS/heter estimator.

ML/hom: number of times when we have no convergence in 5 minutes for the ML–RCM/hom estimator.

ML/het: number of times when we have no convergence in 5 minutes for the ML–RCM/het estimator.

Grad: number of times with numerical problems when evaluating the gradient and/or the log–likelihood for the ML–RCM/hetero estimator. No such problems noticed for the ML–RCM/homo estimator.

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