# Estimators and tests for unbalanced multi-way error component models with correlated effects 

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## 1 Structure of the presentation

- Motivations
- Related literature
- The multiway Error Component Model (ECM)
- Results
- Conclusions


## 2 Motivations

- New a) tests of correlated effects and b) estimators for the (possibly) unbalanced multiway ECM.
- New algebraic results, useful for computations.


## 3 Related literature

- Tests for correlated effects: Hausman (1978), Mundlak (1978), Hausman and Taylor (1982), Kang (1985), Arellano (1993), Ahn and Low (1996), Wooldridge (2002), Krishnakumar (2006).
- Estimators: Kaptein and Wansbeek (1989), Davis (2002).
- Algebra for the multiway ECM: Davis (2002).


## 4 The multiway ECM

### 4.1 Notation for column-wise partitioned matrices

Given a column-wise partitioned matrix $A=\left(\begin{array}{llll}A_{1} & A_{2} & \cdots & A_{m}\end{array}\right)$, define $\mathfrak{D}(A)$ as the set of all column-wise partitioned matrices formed by any number $1 \leq k \leq m$ of distinct blocks of $A$, taken in the same order as in $A$. For example, if $A=\left(\begin{array}{llll}A_{1} & A_{2} & A_{3} & A_{4}\end{array}\right)$, then $\left(\begin{array}{lll}A_{1} & A_{3} & A_{4}\end{array}\right) \in \mathfrak{D}(A)$. $A \in \mathfrak{D}(A)$ and the size of $\mathfrak{D}(A)$ is $\sum_{g=1}^{m}\binom{m}{g}$.

### 4.2 Projection matrices

Given an arbitrary matrix $A, A^{-}$denotes a generalized inverse of $A . P_{[A]}=$ $A\left(A^{\prime} A\right)^{-} A^{\prime}$ indicates the projection matrix onto the space spanned by the columns of $A . Q_{[A]}=I-P_{[A]}$

### 4.3 The Model

I focus on the general multi-way ECM with generic number of levels $m+1$

$$
\begin{equation*}
y=W \delta+\Gamma u \tag{1}
\end{equation*}
$$

where

$$
\begin{aligned}
W & =\left(\begin{array}{ll}
X & \Delta Z
\end{array}\right) \\
\Gamma & =\left(\begin{array}{ll}
I_{n} & \Delta
\end{array}\right) \text { and } \Delta=\left(\begin{array}{llll}
\Delta_{1} & \Delta_{2} & \cdots & \Delta_{m}
\end{array}\right) \\
\delta & =\left(\begin{array}{ll}
\beta^{\prime} & \lambda^{\prime}
\end{array}\right)^{\prime} \\
u & =\left(\begin{array}{llll}
u_{0}^{\prime} & u_{1}^{\prime} & \cdots & u_{m}^{\prime}
\end{array}\right)^{\prime}
\end{aligned}
$$

and

- $\Delta_{i}$ denotes the $\left(n \times g_{i}\right)$ matrix of dummy variables indicating the groups at the level $i=1, \ldots m$
- $u_{i}$ denotes the error component vector of dimension $\left(g_{i} \times 1\right)$;
- $u_{0}$ stands for the idiosyncratic error component vector of dimension $(n \times 1)$

The following identification assumptions holds throughout.
A. 1 Both $X$ and $\Delta Z$ are of full-column rank (f.c.r.).

The following assumption characterises the columns of $X$ as the regressors with idiosyncratic (observation specific) variation.
A. 2 No linear combination of the columns of $X$ lies in the subspace spanned by the columns of $\Delta$.
A. 1 and A. 2 together imply that the regressor matrix $W$ is of f.c.r.
A. 3 ECM variance-covariance matrix of the composite error $\Gamma u$ (Kaptein and Wansbeek, 1987; Davis, 2002)

$$
\begin{equation*}
\Sigma=\sigma_{0}^{2} I_{n}+\sigma_{1}^{2} \Delta_{1} \Delta_{1}^{\prime}+\ldots+\sigma_{m}^{2} \Delta_{m} \Delta_{m}^{\prime} \tag{2}
\end{equation*}
$$

Convenient nonsingular transformations of $\Delta$ and $\Gamma$ are defined below.

Definition 1 Let $\widetilde{\Delta}_{i}=\frac{\sigma_{i}}{\sigma_{0}} \Delta_{i}$ for all $i=1, \ldots, m$. Then, let $\widetilde{\Delta}=\left(\begin{array}{lll}\widetilde{\Delta}_{1} & \cdots & \widetilde{\Delta}_{m}\end{array}\right)$ and $\widetilde{\Gamma}=\left(\begin{array}{cc}I_{n} & \widetilde{\Delta}\end{array}\right)$.

It follows that

$$
\Sigma=\sigma_{0}^{2}\left(I_{n}+\widetilde{\Delta}_{1} \widetilde{\Delta}_{1}^{\prime}+\ldots+\widetilde{\Delta}_{m} \widetilde{\Delta}_{m}^{\prime}\right)
$$

## 5 Algebraic results

Definition 2 Given a real matrix $A$, define the operator $V_{[A]}$ as $V_{[A]}=$ $\left(A A^{\prime}\right)^{-1}$.

The importance of $V_{[\cdot]}$ hinges upon the following

$$
\begin{equation*}
V_{[\widetilde{\Gamma}]}=\sigma_{0}^{2} \Sigma^{-1} \tag{3}
\end{equation*}
$$

$V_{[\cdot]}$ is well defined for any column-wise partitioned matrix $A$ of the form $A=\left(\begin{array}{ll}I & B\end{array}\right)$ as $A A^{\prime}=I+B B^{\prime}$ is positive definite.

The following Lemma (Davis, 2002) is useful to compute $V_{[\widetilde{\Gamma}]}$
Lemma 3 Let $C=\left(\begin{array}{lll}I & D_{1} & D_{2}\end{array}\right)$. Then,

$$
V_{[C]}=V_{\left[I D_{2}\right]}-V_{\left[\begin{array}{ll}
D_{2}
\end{array}\right]} D_{1}\left[I+D_{1}^{\prime} V_{\left[I D_{2}\right]} D_{1}\right]^{-1} D_{1}^{\prime} V_{\left[I D_{2}\right]}
$$

and

$$
V_{\left[I D_{2}\right]}=I-D_{2}\left[I+D_{2}^{\prime} D_{2}\right]^{-1} D_{2}^{\prime}
$$

The following extension to Davis (2002) (and to Wansbeek and Kapteyn (1989)) expands the set of possible representations for $V_{[\widetilde{\Gamma}]}$.

Lemma 4 Given the column-wise partitioned real matrix B, let $B_{1} \in \mathfrak{D}(B)$, $A=\left(\begin{array}{ll}I & B\end{array}\right)$ and $r \equiv \operatorname{rank}\left(B_{1}\right)$. Then, there exists a mapping $m$ : $\mathfrak{L}\left(B_{1}\right) \rightarrow \mathfrak{M}_{r}$ defined as

$$
m\left(B_{1}^{*}\right)=\left\{\begin{array}{cc}
\left(B_{1}^{* \prime} B_{1}^{*}\right)^{-1} B_{1}^{* \prime} B_{1} B_{1}^{\prime} B_{1}^{*}\left(B_{1}^{* \prime} B_{1}^{*}\right)^{-1} & \text { if } B_{1}^{*} \text { has f.c.r. } \\
I_{r} & \text { else }
\end{array}\right.
$$

and such that

$$
\begin{equation*}
V_{[A]}=V_{\left[A \backslash B_{1}\right]}-V_{\left[A \backslash B_{1}\right]} B_{1}^{*}\left[m^{-1}\left(B_{1}^{*}\right)+B_{1}^{* \prime} V_{\left[A \backslash B_{1}\right]} B_{1}^{*}\right]^{-1} B_{1}^{* \prime} V_{\left[A \backslash B_{1}\right]} \tag{4}
\end{equation*}
$$

for all $B_{1}^{*} \in \mathfrak{L}\left(B_{1}\right)$; where $\mathfrak{L}\left(B_{1}\right)$ is the set containing $B_{1}$ and all the submatrices of $B_{1}$ having f.c.r. and $\mathfrak{M}_{r}$ is the collection of all $r \times r$ symmetric positive definite matrices.

Lemma 3 emerges as a corollary of Lemma 4.

A convenient operator is defined.
Given a positive definite symmetric matrix $\Omega$ and any matrix $A$ define $P_{[\Omega, A]}$ as

$$
\begin{equation*}
P_{[\Omega, A]}=A\left(A^{\prime} \Omega A\right)^{-} A^{\prime} \Omega \tag{5}
\end{equation*}
$$

and $Q_{[\Omega, A]}$ as

$$
Q_{[\Omega, A]}=I-P_{[\Omega, A]}
$$

Specific properties of $P_{[\Omega, A]}$ may emerge depending on $A$ and $\Omega$. The following results establishes two important properties for $P_{\left[V_{[\tilde{\Delta}]}, \Delta_{(k)}\right]}$.

Theorem $5 P_{\left[V_{\left.[\tilde{\Gamma}], \Delta_{(k)}\right]}\right]}=P_{\left[V_{\left[\tilde{\Gamma} \backslash \tilde{\Delta}_{(k)}\right]} \Delta_{(k)}\right]}$ for any $\Delta_{(k)} \in \mathfrak{D}(\Delta)$.
Theorem $\left.6 V_{[\widetilde{\Gamma}]} Q_{\left[V_{[\widetilde{\Gamma}]}, \Delta_{(k)}\right]}=V_{\left[\widetilde{\Gamma} \backslash \tilde{\Delta}_{(k)}\right]} Q_{\left[V_{\left[\widetilde{\Gamma} \backslash \tilde{\Delta}_{(k)}\right]}, \Delta_{(k)}\right.}\right]$ for any $\Delta_{(k)} \in \mathfrak{D}(\Delta)$.

## 6 Estimators and tests

### 6.1 Efficient GLS estimators

Under assumptions A.1-A.3, if all effects are not correlated to the regressors, that is if

$$
E(u \mid W)=0
$$

then the Gauss-Marcov estimator for $\beta$ and $\lambda$ is the Multi-way GLS

$$
\begin{equation*}
d^{G L S}=\binom{b^{G L S}}{l^{G L S}}=\left(W^{\prime} V_{[\widetilde{\Gamma}]} W\right)^{-1} W^{\prime} V_{[\widetilde{\Gamma}]} y \tag{6}
\end{equation*}
$$

The formula for $b^{G L S}$ is the following

$$
\begin{equation*}
b^{G L S}=\left(X^{\prime} V_{[\widetilde{\Gamma}]} Q_{\left[V_{[\widetilde{\Gamma}]}, \Delta Z\right]} X\right)^{-1} X^{\prime} V_{[\widetilde{\Gamma}]} Q_{\left[V_{[\widetilde{\Gamma}]}, \Delta Z\right]} y \tag{7}
\end{equation*}
$$

The Multi-way Within estimator for $\beta$ is the following

$$
\begin{equation*}
b^{\text {within }}=\left(X^{\prime} Q_{[\Delta]} X\right)^{-1} X^{\prime} Q_{[\Delta]} y . \tag{8}
\end{equation*}
$$

It is a robust estimator in that it leaves the correlation between regressors and all error components unrestricted. A more general class of efficient estimators encompassing $d^{G L S}$ and $b^{\text {within }}$ as particular cases is derived

Theorem 7 Assume $\boldsymbol{A} .1-\boldsymbol{A} .3$ and let $\Delta_{(k)} \in \mathfrak{D}(\Delta)$. Then, the efficient multi-way GLS estimator for $\beta$ and $\lambda$ in the presence of (possibly) correlated effects at the levels $\Delta_{(k)}, d^{G L S \mid \Delta_{(k)}}$, is

$$
\begin{align*}
d^{G L S \mid \Delta_{(k)}} & =\binom{b^{G L S \mid \Delta_{(k)}}}{l^{G L S \mid \Delta_{(k)}}}  \tag{9}\\
& =\left(W^{\prime} H Q_{\left[H, \Delta_{(k)}\right]} W\right)^{-} W^{\prime} H Q_{\left[H, \Delta_{(k)}\right]} y
\end{align*}
$$

with

$$
\begin{equation*}
b^{G L S \mid \Delta_{(k)}}=\left(X^{\prime} M X\right)^{-1} X^{\prime} M y \tag{10}
\end{equation*}
$$

where $H \equiv V_{\left[\widetilde{\Gamma} \backslash \widetilde{\Delta}_{(k)}\right]}$ and $M=H\left(Q_{\left[H, \Delta_{(k)}\right]}-P_{\left[H_{\left[H, Q_{(k)}\right]} \Delta Z\right]}\right)$.

### 6.2 Between estimators

The Multi-way Between estimator, considering the variation between all groups in $\Delta$, is defined as

$$
\begin{equation*}
\widetilde{d}^{B}=\left(W^{\prime} V_{[\widetilde{\Gamma}]} P_{[\Delta]} W\right)^{-1} W^{\prime} V_{[\widetilde{\Gamma}]} P_{[\Delta]} y . \tag{11}
\end{equation*}
$$

The following general formula for the between estimator of $\beta$ is suggested, which is useful in the context of specification tests

$$
\begin{equation*}
\widetilde{b}^{B\left(\Delta_{(k)}\right)}=\left(X^{\prime} V_{[\widetilde{\Gamma}]} P_{\left[V_{[\widetilde{\Gamma}]}, Q_{\left[V_{[\widetilde{\Gamma}]}, \Delta z\right.}\right]^{\Delta_{(k)}}}\right]^{-1} X^{\prime} V_{[\widetilde{\Gamma}]} P_{\left.\left[V_{\widetilde{\Gamma}]}, Q_{\left[V_{[\widetilde{\Gamma}]}, \Delta z\right.}\right]^{\Delta_{(k)}}\right]} y . \tag{12}
\end{equation*}
$$

It generalizes the extended between estimator derived in Krishnakumar (2006) to an unbalanced multilevel setting with generic non-idiosyncratic variables that do not lie necessarily onto the space spanned by the correlated effects. One can think of $\widetilde{b}^{B\left(\Delta_{(k)}\right)}$ as an estimator that exploits only the residual variation between the groups in $\Delta_{(k)}$ once the variation in $\Delta Z$ has been partialled out (in the metric $V_{[\widetilde{\Delta}]}$ ).

### 6.3 Efficient GLS estimators as weighted averages

Theorem 8 For all $\Delta_{(k)} \in \mathfrak{D}(\Delta)$

$$
b^{G L S}=F b^{G L S \mid \Delta_{(K)}}+(I-F) \widetilde{b}^{B\left(\Delta_{(k)}\right)}
$$

Theorem 9 Let $\Delta_{(\cdot)} \in \mathfrak{D}(\Delta)$ and $\Delta_{(k)} \in \mathfrak{D}\left(\Delta \mid \Delta_{(\cdot)}\right)$ then

$$
b^{G L S \mid \Delta_{(\cdot)}}=F b^{G L S \mid \Delta_{(K)}}+G \widetilde{b}^{B\left(\Delta_{(k)}\right)}-H \widetilde{b}^{B\left(\Delta_{(\cdot)}\right)}
$$

with $F+G+H=I$

### 6.4 Tests for correlated effects

Borrowing the same terminology as Kang's (1985), the following definitions hold.

Definition 10 For some level $i=1, \ldots, m$, the unobserved effect $u_{i}$ is said uncorrelated if $E\left(u_{i} \mid W\right)=0$.

Definition 11 For some level $i=1, \ldots, m$, the unobserved effect $u_{i}$ is said (possibly) correlated if $E\left(u_{i} \mid W\right)$ is left unrestricted.

In a multi-level framework the number of possible specifications for the unobserved effects, $h_{m}$, increases rapidly with the number of error components $m$. For example, Kang (1985) focussing on the two-level model considers $h_{2}=1+\binom{2}{1} 2=5$ possible specifications for the error components and consequently 5 specification tests. These are reported in Table 1.

Table 1: Specification tests in the two-level model

| Test | $\mathrm{H}_{\mathrm{o}}$ | Given: |
| :--- | :--- | :--- |
| 1 | $u_{2}$ uncorrelated | $u_{1}$ correlated |
| 2 | $u_{2}$ uncorrelated | $u_{1}$ uncorrelated |
| 3 | $u_{1}$ uncorrelated | $u_{2}$ correlated |
| 4 | $u_{1}$ uncorrelated | $u_{2}$ uncorrelated |
| 5 | $u_{1}$ and $u_{2}$ uncorrelated |  |

If only $m$ increases to 3 , the number of specification tests increases to $h_{3}=19\left(1+\binom{3}{2} 2+3\left[2+\binom{2}{1}\right]=19\right)$. The specification tests are spelled out in Table 2

Table 2: Specification tests in the three-way model

| Test | $\mathrm{H}_{\mathrm{o}}$ | Given: |
| :--- | :--- | :--- |
| 1 | $u_{3}$ uncorrelated | $u_{1}$ and $u_{2}$ correlated |
| 2 | $u_{2}$ uncorrelated | $u_{1}$ and $u_{3}$ correlated |
| 3 | $u_{1}$ uncorrelated | $u_{2}$ and $u_{3}$ correlated |
| 4 | $u_{3}$ and $u_{2}$ uncorrelated | $u_{1}$ correlated |
| 5 | $u_{3}$ and $u_{1}$ uncorrelated | $u_{2}$ correlated |
| 6 | $u_{1}$ and $u_{2}$ uncorrelated | $u_{3}$ correlated |
| 7 | $u_{3}$ uncorrelated | $u_{1}$ uncorrelated and $u_{2}$ correlated |
| 8 | $u_{3}$ uncorrelated | $u_{2}$ uncorrelated and $u_{1}$ correlated |
| 9 | $u_{2}$ uncorrelated | $u_{1}$ uncorrelated and $u_{3}$ correlated |
| 10 | $u_{2}$ uncorrelated | $u_{3}$ uncorrelated and $u_{1}$ correlated |
| 11 | $u_{1}$ uncorrelated | $u_{2}$ uncorrelated and $u_{3}$ correlated |
| 12 | $u_{1}$ uncorrelated | $u_{3}$ uncorrelated and $u_{2}$ correlated |
| 13 | $u_{3}$ uncorrelated | $u_{1}$ and $u_{2}$ uncorrelated |
| 14 | $u_{2}$ uncorrelated | $u_{1}$ and $u_{3}$ uncorrelated |
| 15 | $u_{1}$ uncorrelated | $u_{2}$ and $u_{3}$ uncorrelated |
| 16 | $u_{3}$ and $u_{2}$ uncorrelated | $u_{1}$ uncorrelated |
| 17 | $u_{3}$ and $u_{1}$ uncorrelated | $u_{2}$ uncorrelated |
| 18 | $u_{1}$ and $u_{2}$ uncorrelated | $u_{3}$ uncorrelated |
| 19 | $u_{1}, u_{2}$ and $u_{3}$ uncorrelated |  |

In general, with $m$ error components the number $h_{m}$ of tests is

$$
\begin{aligned}
h_{m}= & 1+\binom{m}{m-1} 2+\ldots+\binom{m}{2}\left[2+\binom{m-2}{m-3}+\right. \\
& \left.\ldots+\binom{m-2}{2}+\binom{m-2}{1}\right]+m\left[2+\binom{m-1}{m-2}+\right. \\
& \left.\ldots+\binom{m-1}{2}+\binom{m-1}{1}\right] \\
= & 1+\binom{m}{m-1} 2+\sum_{g=1}^{m-2}\binom{m}{m-1-g}\left(2+\sum_{h=1}^{g}\binom{g+1}{h}\right)
\end{aligned}
$$

Fortunately, the notation used in this paper is general enough to deal with any number of error components. Indeed, as large as $h_{m}$ may be, the specification tests can always be classified according to the following four-type partition.

1. Test that the effects at the levels $\Delta_{(\cdot)} \in \mathfrak{D}(\Delta)$ are uncorrelated given that the effects at all other levels $\Delta_{(.)}^{c}$ are uncorrelated. There are $\sum_{g=1}^{m-1}\binom{m}{m-g}$ Hausman tests based on the differences $q_{1}\left(\Delta_{(\cdot)}\right)=b^{G L S}-$ $b^{G L S \mid \Delta_{(\cdot)}}$ over all $\Delta_{(\cdot)} \in \mathfrak{D}(\Delta)$. If $m=2$, these are Test 2 and Test 4 of Table 1. If $m=3$ these are Test 13 to 18 in Table 2.
2. Test that the effects at the levels $\Delta_{(\cdot)} \in \mathfrak{D}(\Delta)$ are uncorrelated, leaving the effects at all other levels, $\Delta \backslash \Delta_{(\cdot)}$, possibly correlated. There are $\sum_{g=1}^{m-1}\binom{m}{m-g}$ Hausman tests based on the differences $q_{2}\left(\Delta_{(\cdot)}\right)=b^{G L S \mid \Delta \backslash \Delta_{(\cdot)}-}$ $b^{\text {within }}$ over all $\Delta_{(\cdot)} \in \mathfrak{D}(\Delta)$. If $m=2$ these are Test 1 and Test 3 of Table 1. If $m=3$, these are Test 1 to 6 of Table 2.
3. Test that the effects at the levels $\Delta_{(k)} \in \mathfrak{D}(\Delta)$ are uncorrelated, maintaining a mixed specification for the effects at all other levels, $\Delta \backslash \Delta_{(k)}$; that is assume that the effects at the levels $\Delta_{(\cdot)} \in \mathfrak{D}\left(\Delta \backslash \Delta_{(k)}\right)$ are uncorrelated and leave the effects at the remaining levels $\Delta \backslash \Delta_{(k)} \backslash \Delta_{(\cdot)}$ possibly correlated, $k=1, \ldots, m-2$. There are

$$
\sum_{g=1}^{m-2}\binom{m}{m-1-g} \sum_{h=1}^{g}\binom{g+1}{h}
$$

Hausman tests based on the differences $q_{3}\left(\Delta_{(\cdot)}, \Delta_{(k)}\right)=b^{G L S \mid \Delta \backslash \Delta_{(k)} \backslash \Delta_{(\cdot)}-}$ $b^{G L S \mid \Delta \backslash \Delta_{(\cdot)}}$ over all $\Delta_{(\cdot)} \in \mathfrak{D}\left(\Delta \backslash \Delta_{(k)}\right)$. If $m=2$, there are no such tests. If $m=3$ these are Test 7 to 12 of Table 2 .
4. Test that the effects at all levels are uncorrelated. Regardless the number of levels in the data, there is 1 Hausman test based on the difference $q_{4}=b^{G L S}-b^{\text {within }}$. This is Test 5 in Table 1 and Tests 19 in Table 2.

Remark 12 Particular tests of type 4 have been examined in the ECM literature, notably Hausman and Taylor (1982), Arellano (1993) and Ahn and Low (1996) for $m=1$ and Kang (1987) for $m=2$. Particular tests of type 1 and 2 have been examined by Kang (1987) for $m=2$. Conversely, tests of type 3 have never been considered, since they emerge only for $m \geq 3$. Given that efficient GLS can be obtained as weighted averages of other estimators, identical tests can be derived using differences that involve the between estimators.

## 7 Conclusion

What's left to do?

- Mata implementation
- Regression based tests a la Mundlak
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