SUR Estimation of Error Components Models With AR(1) Disturbances and Unobserved Endogenous Effects

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Abstract

This paper focusses on the estimation of error components models in the presence of a correlation of the disturbances across equations and AR(1) of the remainder disturbances for panel data with endogenous unobserved effects. Additionally, the set-up allows for unequally spaced panel data and differences in the autocorrelation parameters across equations. The derived procedure is a feasible generalized least squares (GLS) estimator, which provides estimates of the variance components in the spirit of Hausman & Taylor (1981).

Key words: Panel Econometrics; Serial Correlation; Seemingly unrelated regressions; Endogenous effects

JEL classification: C33

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1 Introduction[1]

In several circumstances, a set of equations is to be estimated. Examples are the firm-specific wages of male and female workers, the firm-specific or industry-specific wages of skilled and unskilled workers, bilateral homogeneous and differentiated goods trade, bilateral trade and FDI, etc. For panel data, this can be tackled in a seemingly unrelated regression (SUR) framework following Baltagi (1980).

Noteworthy, some of the mentioned problems typically comprise time-invariant variables of interest[2], which are wiped out by the fixed effects estimator. Examples are experience in earnings equations, distance in bilateral trade equations (homogeneous and intra-industry trade), distance in trade and FDI equations, etc. If the unobserved effects are endogenous, a consistent estimation of the parameters of all (including the time-invariant) variables is still possible, when following the lines of Cornwell et al. (1992) in the spirit of Hausman & Taylor (1981). However, these models assume that there is no autoregressive process in the remainder disturbances and that the only correlation over time is equicorrelation due to the repeated observation of the same cross-sectional units.

This paper introduces serial correlation in the remainder disturbance of SUR models with endogenous unobserved effects, since this is regularly found

[1] I should like to thank Michael Pfaffermayr for helpful comments.

[2] Principally, the problem is that some variables vary only in a single dimension in the N-way panel data case. In applications, this is predominantly the case for time-invariant variables in one-way and two-way panels. Below, I refer to this problem as one of *time-invariant variables.*

in (single-equation) regressions[3] of earnings, bilateral trade, bilateral FDI, etc. Additionally, it allows for unequally spaced panel data, since many data sets contain cross-sectional units with missing observations over time (compare Baltagi & Wu, 1999). Finally and motivated by the empirical evidence, it allows for the possibility of differences in the autocorrelation coefficients across equations. In order to illustrate the requirement of the proposed model, I provide an example from international economics and apply the model to the case of bilateral exports and stocks of outward FDI of the OECD countries estimating a so-called gravity model.

2 The Model

Consider the following set of M equations of an unbalanced panel data regression model (following Baltagi, 1980, 1995 in the notation):

$$y_m = X_m\delta_m + Z_m\zeta_m + u_m \quad (m = 1, ..., M), \tag{1}$$

where y_m is $NT \times 1$, X_m is a $NT \times k'_m$ matrix of time-variant variables, $\delta_m = k'_{1m} \times 1$, $k'_{1m} = k_{1m} + 1$, Z_m is a $NT \times k_{2m}$ matrix of time-invariant variables, $\zeta_m = k_{2m} \times 1$ and

$$u_m = Z_\mu \mu_m + \nu_m \quad (m = 1, ..., M), \tag{2}$$

with $Z_\mu = (I_N \otimes \iota_T)$, ι_T is a vector of ones of dimension T and $\mu'_m = (\mu_{1m}, \mu_{2m}, ..., \mu_{Nm})$ and $\nu'_m = (\nu_{11m}, \nu_{12m}, ..., \nu_{1Tm}, ..., \nu_{NTm})$ and the remainder disturbances ν_{itm} follow a stationary AR(1) process, i.e. $\nu_{itm} =$

[3] More precisely, it would be found in many applications, if it were tested for it.

$\rho_m \nu_{i,t-1,m} + \epsilon_{itm}$ with $|\rho_m| < 1$ and ϵ_{itm} is $IID(0, \sigma^2_{\epsilon m})$. Hence, the autoregressive process (i.e. ρ) might differ across equations.

Similar to Baltagi & Wu (1999), the μ_{im}'s are independent of the ν_{itm}'s, $\nu_{i0m}\tilde{}(0, \sigma^2_{\epsilon m}/(1-\rho^2_m))$. Each cross-sectional unit i observes data at times $t_{i,r}$ for $r = 1, ..., n_i$ with $1 = t_{i,1} < ... < t_{i,n_i} = T_i$, where $n_i > K$ for $i = 1, 2, ...N$. Hence, the data may be unequally spaced, but in this respect the equations $(m = 1, ..., M)$ are identical. The covariance matrix reads

$$E \begin{pmatrix} \mu_m \\ \nu_m \end{pmatrix} \begin{pmatrix} \mu'_l & \nu'_l \end{pmatrix} = \begin{bmatrix} \sigma^2_{\mu_{ml}} I_N & 0 \\ 0 & \sigma^2_{\nu_{ml}} I_{NT} \end{bmatrix}$$

for $m, l = 1, 2, ...M$. To obtain homoskedastic residuals over time in each equation, we have to premultiply the regression model (1) for each equation m by the block-diagonal matrix $diag[C^*_{im}(\rho_m)]$, which is $n_i \times n_i$ and

$$C^*_{im}(\rho_m) = (1-\rho^2_m)^{1/2} \cdot \tag{3}$$

$$\begin{bmatrix} 1 & 0 & ... & 0 & 0 \\ -\left(\frac{\rho_m^{2(t_{i,2}-t_{i,1})}}{1-\rho_m^{2(t_{i,2}-t_{i,1})}}\right)^{1/2} & \left(\frac{1}{1-\rho_m^{2(t_{i,2}-t_{i,1})}}\right)^{1/2} & ... & 0 & 0 \\ . & . & ... & . & . \\ 0 & 0 & ... & . & 0 \\ 0 & 0 & ... & -\left(\frac{\rho_m^{2(t_{i,n_i}-t_{i,n_{i-1}})}}{1-\rho_m^{2(t_{i,n_i}-t_{i,n_{i-1}})}}\right)^{1/2} & \left(\frac{1}{1-\rho_m^{2(t_{i,n_i}-t_{i,n_{i-1}})}}\right)^{1/2} \end{bmatrix},$$

which is a modified Prais-Winsten transformation as proposed in Baltagi & Wu (1999) for the single-equation case. The transformed, equation-specific disturbances read

$$u^*_m = diag\left[C^*_{im}(\rho_m)\right] u_m = diag\left[C^*_{im}(\rho_m)\right] diag(\iota_{n_i})\mu_m + diag\left[C^*_{im}(\rho_m)\right] v_m, \tag{4}$$

where ι_{n_i} is a vector of ones of dimension n_i, which is equivalent for i across equations, and we treat the equations as independent for the moment. Define

$$\begin{aligned} g_{im} &= [C^*_{im}(\rho_m)]\,\iota_{n_i} \\ &= (1-\rho_m^2)^{1/2}\left(1, \frac{1-\rho_m^{(t_{i,2}-t_{i,1})}}{(1-\rho_m^{2(t_{i,2}-t_{i,1})})^{1/2}}, \ldots, \frac{1-\rho_m^{(t_{i,n_i}-t_{i,n_i-1})}}{(1-\rho_m^{2(t_{i,n_i}-t_{i,n_i-1})})^{1/2}}\right)' \end{aligned} \quad (5)$$

and

$$G_i = (g_{i1}, g_{i2}, \ldots, g_{iM}) \quad (6)$$

$$P_i = G_i(G_i'G_i)^{-1}G_i \quad (7)$$

$$Q_i = I_{n_i} - P_i. \quad (8)$$

Noteworthy, G_i, P_i and Q_i are $n_i \times n_i$ matrices and P_i and Q_i account for the equation-specific autocorrelation process (ρ_m). G_i is not diagonal, which is different from Baltagi & Wu (1999). If ρ is identical across equations, the off-diagonal entries of P are identical (for Q the same holds true) with balanced panel data. The variance-covariance matrix of the set of M equations is block-diagonal as long as the data are sorted first by cross-sectional units (i) and then by time (t) and equation (m). The individual-specific transformation matrix (i.e. each diagonal block of the whole matrix) is then defined by

$$\Omega_i^* = \Sigma(u_i^* u_i^{*\prime}) = \Sigma_\mu \otimes (I_{n_i} \otimes J_T) + \Sigma_\nu \otimes (I_{n_i} \otimes I_T). \quad (9)$$

Similar to Baltagi (1980), we can reformulate this to obtain

$$\Omega_i^* = \Sigma_{1i} \otimes P_i + \Sigma_\nu \otimes Q_i \quad (10)$$

and

$$\Omega_i^{*-1/2} = \Sigma_{1i}^{-1/2} \otimes P_i + \Sigma_\nu^{-1/2} \otimes Q_i. \tag{11}$$

One can estimate the required variance components matrices in the following way. First, estimate

$$y_{i,t_{i,r,m}}^{W**} = y_{i,t_{i,j},m}^{*} - g_{i,r,m}\left(\sum_{s=1}^{n_i} g_{i,s,m} y_{i,t_{i,s},m}^{*}\right) / \left(\sum_{s=1}^{n_i} g_{i,s,m}^2\right) \tag{12}$$

to obtain the Within residuals in the spirit of Amemiya (1971). The first (remainder) error component matrix is estimated from the residuals of the transformed first-stage regression (12):

$$\widehat{\Sigma}_\nu = V^{**\prime} V^{**} / \sum_{i=1}^{N} (n_i - 1), \tag{13}$$

with $V^{**} = [v_1^{**}, ..., v_M^{**}]$ denoting the $n_i \cdot N \times M$ matrix of the least-squares dummy variable type residuals from the fixed effects AR(1) regression of each of the m equations. Take pseudo-averages of the Amemiya (1971) type residuals from this regression over time (i.e. calculate $u_i^{**\prime}(g_i(g_i' g_i)^{-1} g_i')$ and run 2SLS of these residuals on the *singly exogenous*, time-invariant, transformed variables as suggested in (3) with the *doubly exogenous*, equivalently transformed time-variant variables as instruments.[4] This regression not only obtains a parameter estimate for the time-invariant variables, but it also produces residuals (η_{im}^{**}), which serve to derive the second required variance component.[5] An estimate of this variance component is

$$\widehat{\Sigma}_{1i} = H' P_i H / N, \tag{14}$$

[4]Following Cornwell et al. (1992), I label the exogenous variables, which are correlated with the error term, as *singly exogenous* and the uncorrelated ones as *doubly exogenous*.

[5]If the number of *doubly exogenous* variables is larger than the number of *singly ex-*

where $H = [\eta_1^{**}, ..., \eta_M^{**}]$ is a $n_i \cdot N \times M$ matrix with the vectors of the second-stage, pseudo-averaged between-residuals as its entries. Finally, the cross-sectional variance component is

$$\widehat{\Sigma}_\mu = \left(\sum_i^N \widehat{\Sigma}_{1i} - N \widehat{\Sigma}_\varepsilon \right) \left(\sum_{i=1}^N G_i' G_i \right)^{-1} . \tag{15}$$

Using the result from Prucha (1984), this estimator is an asymptotically efficient, feasible SUR-GLS estimator, as long as Σ_ν is estimated consistently and Σ_μ has a positive definite limit.

Finally, transform the full model by $\Omega^{*-1/2}$ and run 2SLS on the explanatory (*singly* and *doubly exogenous*, time-variant and time-invariant) variables using three sets of instruments (compare Breusch et al., 1989).[6] First, both the transformed within components and the transformed between components of the *doubly exogenous* variables. Second, the transformed within components of the *singly exogenous* variables. Third the transformed time-invariant but *doubly exogenous* variables. Of course, time-invariant *singly exogenous* variables cannot serve as instruments.

ogenous, time invariant variables, this always obtains an estimate of the second variance component, which is superior to the traditional one. I.e. it is consistent or at least closer to the consistent one than the traditional estimate as used in a simple random effects SUR AR(1) model.

[6]Equivalently, one could use the more efficient sets of instruments as suggested by Amemiya & MaCurdy (1986) or Breusch et al. (1989), which require more exogeneity assumptions.

3 An Example

To give an example, I estimate the impact of bilateral distance (D), sum of real bilateral GDP (G), relative country size in terms of real GDP (S), the bilateral distance in relative factor endowments (real GDP per capita; R), viability of contracts (V) and rule of law (R) on both real bilateral exports and stocks of outward FDI of the OECD countries over the period 1986-1997 (compare Markusen & Maskus, 1999, for the motivation of a similar specification).[7] I refer the reader to the Appendix for details on the variable construction and data sources. All variables are in logs. I include only bilateral relations, which are observed in at least five years. In general terms, the specifications read

$$E_{ijt} = \beta_0^E + \gamma_1^E D_{ij} + \beta_1^E G_{ijt} + \beta_2^E S_{ijt} + \beta_3^E R_{ijt} + \beta_4^E V_{it} + \beta_5^E V_{jt} + \beta_6^E R_{it} + \beta_7^E R_{jt} \quad (16)$$
$$+ \lambda_t^E + u_{ijt}^E$$
$$F_{ijt} = \beta_0^F + \gamma_1^F D_{ij} + \beta_1^F G_{ijt} + \beta_2^F S_{ijt} + \beta_3^F R_{ijt} + \beta_4^F V_{it} + \beta_5^F V_{jt} + \beta_6^F R_{it} + \beta_7^F R_{jt} \quad (17)$$
$$+ \lambda_t^F + u_{ijt}^F,$$

with $u_{ijt}^E = \mu_{ij}^E + \varepsilon_{ijt}^E$ and $u_{ijt}^F = \mu_{ij}^F + \varepsilon_{ijt}^F$, subscript i (j) runs over exporters (importers), t denotes years, and superscript E (F) refer to exports and FDI. I estimate three different AR(1) models, which all allow for unequally spaced data. Two of them are single equation regressions: a fixed

[7] Bilateral trade (and FDI) models, which inter alia include distance and country size as determinants are known as gravity models, since they come close to the idea of Issac Newton's law of gravity.

effects AR(1) approach (FEM-AR), which does not obtain an estimate of the time-invariant distance variable, and an AR(1) model in the spirit of Hausman & Taylor (1981; HTM-AR), which does. The third approach is a Hausman & Taylor SUR model (HTM-SUR-AR), which takes the interdependencies of exports and outward FDI (i.e. the cross-equation correlations of the errors) into account and allows for different autocorrelation coefficients and unequally spaced panel data altogether. The corresponding estimated variance components are

$$\widehat{\Sigma}_\mu = \begin{bmatrix} 17.2435 & 12.9750 \\ 12.9750 & 13.2507 \end{bmatrix}; \quad \widehat{\Sigma}_\varepsilon = \begin{bmatrix} .0352 & .0021 \\ .0046 & .2278 \end{bmatrix}. \tag{18}$$

$>$ Table 1 $<$

Table 1 presents the estimation results. The parameter estimates of the so-called Heckscher Ohlin variables (G, S, R) are widely in accordance with the theoretical hypotheses (we would expect positive signs throughout). D, V, and R represent impediments to trade and FDI. Nonetheless, a positive impact does not square with theory, as long as these determinants affect both variable trade and fixed investment costs together.

I should like to underpin the following important results. First, the equivalence of the estimated autocorrelation coefficients is significantly rejected on the basis of a χ^2 test (compare Footnote *d)* in Table 1). Second, according to the Hausman tests in the underlying example there is no way to obtain consistent estimates of the parameters from standard, single equation AR(1) error components models as suggested by Baltagi & Wu (1999). Third, the estimated HTM-AR and HTM-SUR-AR models treat only distance (D) and the bilateral sum of GDP (G) as *singly exogenous* and all other determinants as *doubly exogenous*. The appropriateness of this decision is not rejected in terms of the Hausman & Taylor (1981) over-identification tests, and the geometric mean of the canonical correlation coefficients indicates a high relevance of the instruments.[8] Fourth, the instruments are even more powerful in the HTM-SUR-AR and the appropriateness of the single-equation HTM-AR models is rejected on the basis of a familiar Honda (1985) test. The latter is based on the square root of the Breusch-Pagan test statistic and normally distributed with the null that the off-diagonal element of the estimated $\widehat{\Sigma}_1$ matrix is zero.

These results clearly indicate that for the present example other related estimation techniques would have failed to provide consistent[9] or at least efficient[10] parameter estimates of all variables of interest. In the econometrics of international trade, similar problems could arise when analysing the joint determinants of inter-industry and intra-industry trade. The determinants of high-skilled and low-skilled wages, employment or wage bills constitute related examples in labor economics.

[8] Bowden & Turkington (1984) suggest this as a measure of instrumental quality. Compare also Baltagi & Khanti-Akom (1990) for an application in the Hausman & Taylor (1981) set-up.

[9] Concerning single-equation AR(1) error components parameter estimates as suggested by Baltagi & Wu (1999).

[10] Regarding the parameter estimates as derived from a SUR model without AR(1) in the spirit of Cornwell et al. (1992).

4 Conclusions

This paper considers an error components SUR framework, which allows for serial correlation in the classical error term. The autocorrelation coefficients are allowed to differ across equations and the data may be unequally spaced in the time dimension. The starting point is a model in the spirit of Hausman & Taylor (1981) and Cornwell et al. (1992), which is superior to the traditional error components model, since the latter often obtains only biased estimates due to correlation between the exogenous variables and the panel effects. The chosen approach is able to overcome this shortcoming via instrumental variable techniques. If enough viable instruments are available, the obtained estimator is efficient and consistent. Additionally and in contrast to the fixed effects AR(1) model, it obtains parameter estimates of the time-invariant variables and is efficient.

An example from international economics underpins the importance and the requirement of the chosen approach. Bilateral exports and outward FDI exhibit different autocorrelation coefficients. Both depend on the time-invariant distance. A couple of tests indicate that (i) the fixed effects AR(1) estimator seems not efficient, (ii) the error components AR(1) model is inconsistent, (iii) the cross-equation error components are important. The suggested Hausman & Taylor (1981) and Cornwell et al. (1992) SUR AR(1) type model is therefore superior to the other considered models, and there are a couple of other natural candidate problems from international or labor economics, which might share this property.

5 References

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6 Appendix: Variable Definitions and Data Sources

Real stocks of FDI are calculated on the basis of nominal stocks of FDI and Investment deflators (certainly, this is only a rough but frequently used measure of real stocks of outward FDI). Distance is the greater circle distance between two countries' capitals. I follow Helpman (1987) in the definition of the three Heckscher-Ohlin variables:

$$G_{ijt} = \log(GDP_{it} + GDP_{jt}) \tag{19}$$

$$S_{ijt} = \log\left[1 - \left(\frac{GDP_{it}}{GDP_{it} + GDP_{jt}}\right)^2 - \left(\frac{GDP_{jt}}{GDP_{it} + GDP_{jt}}\right)^2\right] \tag{20}$$

$$R_{ijt} = \left|\log\left(\frac{GDP_{it}}{N_{it}}\right) - \log\left(\frac{GDP_{jt}}{N_{jt}}\right)\right|, \tag{21}$$

where GDP is real gross domestic product, N is population, and subscripts i, j and t run over exporters, importers, and years. All other variables are in logs as well and Table 2 provides information about data sources.

> Table 2 <

Table 1: AR(1) Panel Regression Results for Bilateral Exports and FDI (Real Figures and Variables in Logs)

	Real bilateral exports			Real bilateral stocks of outward FDI		
	Within	Hausman-Taylor [b]	Hausman-Taylor [c] SUR	Within	Hausman-Taylor [b]	Hausman-Taylor [c] SUR
Independent Variables[a]						
Distance (D_{ij})	-	-1.038 **)	-0.268	-	-2.717 ***)	-3.912 ***)
	-	(0.438)	(0.599)	-	(0.453)	(0.577)
Sum of bilateral GDP (G_{ijt})	3.331 ***)	2.924 ***)	2.889 ***)	2.251 ***)	3.087 ***)	3.535 ***)
	(0.204)	(0.143)	(0.152)	(0.555)	(0.275)	(0.328)
Similarity in country size (S_{ijt})	0.894 ***)	1.010 ***)	1.059 ***)	0.532	0.565 ***)	0.354
	(0.148)	(0.100)	(0.107)	(0.395)	(0.178)	(0.220)
Distance in GDP per capita (R_{ijt})	-0.086	0.146 *)	0.171 *)	-0.044	0.397 ***)	0.359 *)
	(0.124)	(0.084)	(0.090)	(0.327)	(0.152)	(0.183)
Exporter viability of contracts (V_{it})	-0.227 *)	-0.242 **)	-0.259 **)	-0.974 ***)	0.571 *)	0.438
	(0.136)	(0.114)	(0.115)	(0.354)	(0.324)	(0.352)
Importer viability of contracts (V_{jt})	0.451 ***)	0.507 ***)	0.504 ***)	0.223	0.315 ***)	0.245 *)
	(0.059)	(0.041)	(0.041)	(0.162)	(0.117)	(0.126)
Exporter rule of law (R_{it})	-0.234 ***)	-0.238 ***)	-0.244 ***)	-0.184	-0.190	-0.203
	(0.064)	(0.055)	(0.056)	(0.159)	(0.150)	(0.162)
Importer rule of law (R_{jt})	0.001	-0.043	-0.042	-0.038	-0.057	-0.067
	(0.056)	(0.042)	(0.043)	(0.150)	(0.121)	(0.131)
Observations	2882	3235	3235	2882	3235	3235
R^2	0.94	0.82	0.76	0.87	0.83	0.70
Autocorrelation (ρ)[d]	0.54	-	-	0.66	-	-
Bhargava et al. (1984)	1.01	-	-	0.79	-	-
Baltagi & Wu (1999): LBI	1.38	-	-	1.19	-	-
Time effects[e]	3.78 ***)	6.07 ***)	6.41 ***)	5.44 ***)	11.04 ***)	8.20 ***)
Bilateral effects: F(352,2512)	71.31 ***)	-	-	15.96 ***)	-	-
Hausman test: $\chi^2(17)$	49.89 ***)	-	-	70.06 ***)	-	-
Overidentification: $\chi^2(5)$	-	2.27	-	-	8.87	-
Canonical correlations[f]	-	0.71	0.82	-	0.57	0.59

a) Standard errors in parantheses. Fixed time effects, bilateral effects and constant not reported for the sake of brevity. - b) The average estimated θ is 0.97 in the export model and 0.88 in the FDI model. - c) A Honda test on the restriction of zero off-diagonal elements of the estimated Σ_1 matrix obtains a test statistic of 52.44, which is standard normally distributed. - d) Calculated on the basis of ρ = 1-D/2, where D is the Durbin -Watson statistic. A test on the estimated $\rho_{exports} = \rho_{FDI}$ yields a test statistic of 23.88 and is distributed as $\chi^2(1)$. - e) Distributed as F(10,2512) in the fixed effects models and as F(11,3215) in the other models. - f) Geometric mean of canonical correlation coefficients.

***) significant at 1%; **) significant at 5%; *) significant at 10%;

Table 2: Data Sources

Source	
Economic Freedom Network	A country's viability of contracts and rule of law
IMF (International Financial Statistics)	Nominal GDP in US $, GDP deflators, population, investment deflators, exchange rate indices
IMF (Direction of Foreign Trade)	Nominal exports in US $ and export price deflators
OECD (Monthly Statistics of international Trade)	Nominal exports in US $ and export price deflators
OECD (Economic Outlook and National Accounts, Volume 1)	Nominal GDP in US $, GDP deflators, population, investment deflators
OECD (International Direct investment Statistics Yearbook)	Nominal stocks of outward FDI in US $
Vienna Institute of Comparative Economic Studies	Nominal exports in US $, export price deflators, exchange rate indices, investment deflators and population of Central and Eastern European Countries