



ISTITUTO DI STUDI E ANALISI ECONOMICA

**Unit root and cointegration tests for
cross-sectionally correlated panels.
Estimating regional production functions**

by

Roberto Basile

ISAE, Piazza dell'Indipendenza, 4, 00185 Rome (Italy)
and University of Macerata (Italy)

Mauro Costantini

ISAE, Piazza dell'Indipendenza, 4, 00185 Rome (Italy)
and University of Rome La Sapienza (Italy)

Sergio Destefanis

University of Salerno (Italy)

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ISAE - Piazza dell’Indipendenza, 4 – 00185 Roma.

Tel. +39-06444821; www.isae.it

ABSTRACT

This paper employs recently developed non stationary panel methodologies that assume some cross-section dependence to estimate the production function for Italian regions in the industrial sector over the period 1970-1998. The analysis consists in three steps. First, unit root tests for cross-sectionally dependent panels are used. Second, the existence of a cointegrating relationship between value added, physical and human capital variables is investigated. The Dynamic OLS (DOLS) and Fully modified (FMOLS) estimators developed by Pedroni (1996, 2000, 2001) and the Panel Dynamic OLS (PDOLS) estimator proposed by Mark and Sul (2003) are then used to estimate the long run relationship between the variables considered.

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1 INTRODUCTION

There is a plethora of studies which estimate aggregate production functions using macro panel data for countries or regions (e.g. Aschauer, 1989; Holtz-Eakin, 1994; Islam, 1995; Garcia-Mila, McGuire and Porter, 1996). More recent works consider non-stationary panel data techniques (e.g. McCoskey and Kao, 1999; Canning, 1999; Marrocu, Paci and Pala, 2000). All of them assume the hypothesis of cross-section independence. Here, we claim that the independence assumption is too strong, especially when regional data are used, since co-movements of economic variables between one region and another are usually observed because of spill-over effects. For instance, it is not the case to test the stationarity of the GDP, or other macroeconomics variables, of one region without taking into account the relationship between this GDP and the GDP of the other regions belonging to the same country.

In this paper, a regional production function in the industrial sector is estimated for Italian regions over the period 1970-1998 by using recent non-stationary panel estimators that assume some sort of cross-section dependence. The analysis consists in three steps. First, unit roots properties of the panel dataset are properly investigated by applying newly developed tests for cross-sectionally dependent panels. Second, the existence of a cointegrating relationship between value added, physical and human capital variables is also investigated in a cross-section dependence framework. Finally, the Dynamic OLS (DOLS) and Fully modified (FMOLS) estimators constructed by Pedroni (1996, 2000, 2001) and the Panel dynamic OLS estimator (PDOLS) (Mark and Sul, 2003) are used in order to estimate the long run relationship between the variables considered¹. All the estimators take into account some degree of cross-section dependence.

Our results provide robust evidence in favor of a cointegrating relationship between regional value added, physical capital and human capital-augmented labor. The estimated long-run input elasticities suggests that allowance for common time effects and individual trends usually implies that the regional production function is characterized by constant returns to scale. Otherwise, the production function exhibits slightly increasing returns to scale.

The paper is organised as follows. Section 2 describes the model. Section 3 discusses the econometric methodology. Data and empirical results are presented in Section 4. Section 5 concludes.

¹ The PDOLS estimator is a within dimension panel estimator. The DOLS and FMOLS estimators proposed by Pedroni (2000, 2001) are between estimators.

2 THE MODEL

We estimate a Cobb-Douglas production function for the Italian regions adopting the human capital specification suggested by Hall and Jones (1999):

$$Y_{i,t} = A_{i,t} (K_{i,t})^\alpha (L_{i,t} h_{i,t})^\beta \quad (1)$$

where $Y_{i,t}$ is the value added in region i at time period t , $K_{i,t}$ is the stock of physical capital and $L_{i,t} h_{i,t}$ is the amount of human capital-augmented labour used in production (with $h_{i,t}$ the human capital per worker and $L_{i,t}$ the total number of workers). $A_{i,t}$ is the specification for (Hicks-neutral) technology and it is the element which introduces a stochastic term into the model. Specifically, we define a simple knowledge production function for region i at time t as follows:

$$A_{i,t} = e^{\gamma_i + \delta_i t + \theta_t + \varepsilon_{i,t}} \quad (2)$$

where γ_i is a region-specific constant which captures the intrinsic efficiency in technology production, the component $\delta_i t$ catches the growth path of region-specific efficiency in producing technology, θ_t captures the worldwide (or countrywide) knowledge accumulation and $\varepsilon_{i,t}$ introduces a random shock in the knowledge production function. The common time effect θ_t is introduced since we assume that some technology spreads across regional boundaries through international and interregional trade which also implies that regional economies cannot be regarded as technologically independent. Therefore, the regional production function is estimated taking into account the cross-regional dependence².

² Obviously, this represents a very simple way of modelling technology. First, in our model, technology and technological change are completely exogenous. Specifically, we decided not to endogenize technological change (for example by introducing R&D investments within the knowledge production function), since we do not have data on technology (such as R&D expenditure or number of patents) at regional level for the whole time period considered in the empirical analysis. Second, the assumption of Hicks-neutral technological progress implies that technological change is fully disembodied and it depends only on time.

As usual, labour $L_{i,t}$ is assumed to be homogenous within a region and $h_{i,t}$ is a transformation of $E_{i,t}$ that measures the education level of each labour unit in terms of years of schooling. Thus, human capital-augmented labour is given by

$$L_{i,t}h_{i,t} = L_{i,t}e^{\phi(E_{i,t})}$$

In this specification, the function $\phi(E)$ reflects the efficiency of a labour unit with E years of schooling relative to one with no education ($\phi(0)=0$). The derivative is the return to schooling estimated in a Mincerian wage regression: an additional year of schooling raises a worker's efficiency proportionally by $\phi'(E)$.

Taking logs, equation (1) can be written as follows:

$$\ln Y_{i,t} = \gamma_i + \delta_i t + \theta_t + \alpha \ln K_{i,t} + \beta \ln L_{i,t}h_{i,t} + \varepsilon_{i,t} \quad (3)$$

The panel model includes a region-specific effect γ_i , a region-specific linear trend $\delta_i t$ and a common time-specific factor θ_t . The two parameters α and β can be interpreted as the elasticities of physical and human capital with respect to production output.

In this paper, equation (3) is estimated by using a panel data set of 20 Italian regions over the period 1970-1998. Several approaches have been used in the literature to study aggregate production functions. Mankiw, Romer and Weil (1992) estimate a cross-country production function for physical and human capital. Aschauer (1989), Holtz-Eakin (1994), Garcia-Mila and McGuire and Porter (1996) estimate production function models including public capital infrastructure using data on the US States (all these studies do not explicitly consider the non-stationary nature of the data). Canning (1999) uses annual cross-country data for the period 1960-1990 to analyse an aggregate production function incorporating labour, physical capital, human capital and infrastructure adopting non-stationary panel data approaches under the assumption of cross-section independence. McCoskey and Kao (1999) estimate a production function incorporating capital, labour and a measure of the urbanization level adopting non-stationary panel data approaches under the assumption of cross-section independence.

A methodology alternative to the econometric estimation of production function is the so-called "level accounting" approach (e.g. Hall and Jones, 1999 and Aiello and Scoppa, 2000). This methodology has been criticized on the

grounds of the restrictive assumptions needed for the computation of the Solow residual. For example, under the hypothesis of constant return to scale (i.e. $\beta=1-\alpha$) and a fixed value for the α parameter, Hall and Jones (1999) calculate the level of total factor productivity (TFP) for a sample of OECD countries. In particular, they use a human-capital augmenting production function, like the one reported in equation (1), but with a Harrod-neutral technology and with the assumption of constant return to scale. This specification allows them to decompose differences in output per worker across countries into differences in the capital-output ratio, differences in educational attainment and differences in TFP.

The same approach has been used by Aiello and Scoppa (2000) to derive the TFP for Italian regions. They have used the national capital elasticity (given by the ratio of gross profits to value added, set equal to 0.38) to all the Italian regions in order to compute the regional TFP levels. As already emphasised by Marrocu *et al.* (2000), this procedure has a crucial weakness since it does not take into account the high heterogeneity among regions and sectors. However, Marrocu *et al.* uses a non-stationary panel approach for cross-sectional independence.

Following the estimation approach rather than “level accounting” approach, in the present paper no restrictive assumptions on the parameters are imposed and, in particular, the hypothesis of constant return to scale is released. Working with a long panel dataset, methods for non-stationary panels which allow the inclusion of the effect of common time are used. In such a way, the effect of some cross-regional dependence is captured³.

3 ECONOMETRIC METHODOLOGY

The empirical analysis consists in three steps. First, the panel properties of the variables are properly investigated. In the first generation of panel unit root (Levin and Lin, 1992, 1993; Levin, Lin and Chu, 2002; Im, Pesaran and Shin, 1997, 2003; Choi, 2001; Maddala and Wu, 1999) correlations across units constitute nuisance parameters. The cross-sectional independence hypothesis is rather restrictive and somewhat unrealistic in the majority of macroeconomic

³ Another problem pertains to the direction of causality in the relationship between output and physical and human capital. Capital inputs may determine output, but output may have a feedback into capital accumulation. Thus, when we estimate equation (3), possible endogeneity problems might be solved using dynamic OLS estimators.

applications of unit root tests (Phillips and Sul, 2003; O'Connell, 1998), where co-movements of economies are often observed. Rather than considering correlations across units as nuisance parameters, the second generation of panel unit root (Phillips and Sul, 2003; Chang, 2002 and 2003; Choi, 2004a; Bai and Ng, 2003; Moon and Perron, 2004; Pesaran, 2005)⁴ aims at exploiting these co-movements in order to define new test statistics. In this paper four cross-sectional dependent panel unit root tests are performed: Choi (2004a, hereafter CH), Bai and Ng (2003, hereafter BNG), Moon and Perron (2004, hereafter MP) and Pesaran (2005, hereafter PS)⁵. Second, a set of panel cointegration tests are applied. The ADF test (Kao, 1999) and the WR_M test (Westerlund, 2004) are applied. In Kao (1999) the hypothesis of homogeneity of the cointegrating vector among individual members of the panel is assumed. The WR_M test allows for cross-sectional dependence.

Finally, the long run relationship is estimated by using the DOLS and FMOLS estimators developed by Pedroni (1996, 2000 and 2001, hereafter PED) and the PDOLS estimator provided by Mark and Sul (2003, hereafter MS). In the PED and MS approaches a certain form of cross-sectional dependence through the presence of common time effects is assumed.

3.1 Panel unit root with cross-sectional dependence

CH proposed new panel unit root tests for cross-sectionally correlated panels. The cross-sectional correlation is modelled by a two-way error-component model. The test statistics are derived from combining p-values from the Augmented Dickey-Fuller test applied to each time series whose non-stochastic trend components and cross-correlation are eliminated by Elliot, Rothenberg and Stock's (1996) GLS-based de-trending and the conventional cross-sectional demeaning panel data.

⁴ A macroeconomics application is, e.g. in Hurlin (2004).

⁵ Gutierrez (2003) shows that the Moon and Perron (2004) tests have good size and power in finite samples for different specifications and different values of T and N, and that the Bai and Ng's (2004) pooled tests of the null hypothesis that idiosyncratic components are non-stationary also have good size and power, especially when the Dickey-Fuller-GLS version of the test is used, while the ADF test used to analyze the nonstationary properties of the common component has low power. The Choi's (2004) tests are largely oversized. Gutierrez shows that all tests lack power when a deterministic trend is included in the data generating process.

The panel unit root tests developed by CH are:

$$P_m = -\frac{1}{\sqrt{N}} \sum_{i=1}^N (\ln(p_i) + 1) \quad (4)$$

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^N \Phi^{-1}(p_i) \quad (5)$$

$$L^* = \frac{1}{\sqrt{\pi^2 N/3}} \sum_{i=1}^N \ln\left(\frac{p_i}{1-p_i}\right), \quad (6)$$

where P_m test is a modification of Fisher (1932) inverse chi-square, $\Phi(\cdot)$ is the standard normal cumulative distribution function, p_i indicates the asymptotic p-value of the Dickey-Fuller-GLS test for region i ⁶. For $T \rightarrow \infty$ and $N \rightarrow \infty$,

$$P_m, Z, L^* \Rightarrow N(0,1)$$

BNG consider the factor model:

$$Y_{it} = D_{it} + \lambda_i' F_t + e_{it} \quad (7)^u$$

where D_{it} is a polynomial trend function, F_t is an $r \times 1$ vector of common factors, and λ_i is a vector of factor loading. Thus the series Y_{it} is decomposed into three components: a deterministic one, a common component with factor structure and an idiosyncratic error component. The process Y_{it} may be non-stationary if one or more of the common factors are non-stationary, or the idiosyncratic error is non-stationary, or both. To test the stationarity of the idiosyncratic component, BNG propose to pool the individual ADF t-statistics with de-factored estimated component e_{it} in a model with no deterministic trend:

$$\Delta e_{it} = \delta_{i,0} \hat{e}_{i,t-1} + \sum_{j=1}^p \delta_{i,j} \Delta \hat{e}_{i,t-j} + u_{i,t} \quad (8)$$

BNG developed a test in order to test the common factor and the idiosyncratic error separately. Let $ADF_{\hat{e}}^c(i)$ be the ADF t-statistic for the i -th

⁶ The percentiles of the asymptotic p-values of the Dickey-Fuller-GLS tests are simulated by Choi.

region. The asymptotic distribution of the $ADF_{\hat{e}}^c(i)$ coincides with the Dickey-Fuller distribution for the case of no constant. However, these individual time series tests have the same low power as those based on the initial series. BNG proposed pooled tests based on Fisher's type statistics defined as in Choi (2001) and Maddala and Wu (1999). Let $P_{\hat{e}}^c$ be the p-value associated with $ADF_{\hat{e}}^c(i)$, then

$$Z_{\hat{e}}^c = \frac{-2 \sum_{i=1}^N \log p_{\hat{e}}^c(i) - 2N}{\sqrt{4N}} \xrightarrow{D} N(0,1) \quad (9)$$

MP developed several unit root tests in which the cross-sectional units are correlated. To model the cross-sectional dependence, MP provided an approximate linear dynamic factor model in which the panel data are generated by both idiosyncratic shocks and unobservable dynamic factors that are common to all individual units. In our analysis, we apply the following tests:

$$t_a^* = \frac{\sqrt{NT}(\hat{\rho}_{pool}^+ - 1)}{\sqrt{\frac{2\hat{\phi}_e^4}{\hat{\omega}_e^4}}} \quad (10)$$

$$t_b^* = \sqrt{NT}(\hat{\rho}_{pool}^+ - 1) \sqrt{\frac{1}{NT^2} \text{tr}(Y_{-1} Q_B Y_{-1}') \left(\frac{\hat{\omega}_e^2}{\hat{\phi}_e^4} \right)} \quad (11)$$

where $\hat{\rho}_{pool}^+$ is the bias-corrected pooled autoregressive estimated of ρ_{pool}^+ , $\hat{\omega}_e^2$ and $\hat{\phi}_e^4$ are respectively the estimates of the cross sectional average of long run variance of \hat{e}_{it} and the cross sectional average of $\hat{\omega}_{e,i}^4$.

PS used a different method for dealing with the problem of cross-section dependence. Instead of basing the unit root tests on deviations from the estimated factors, PS augments the standard DF (or ADF) regression with the cross section averages of lagged levels and first-differences of the individual series. The panel unit root tests are then based on the average of individual cross-sectionally augmented ADF statistics (CADF). The individual CADF statistics may be used to construct modified versions of the t-bar test developed by Im, Pesaran and Shin (2003), the inverse chi-square test (P test) developed

⁷ See appendix.

by Maddala and Wu (1999) and the inverse normal test (Z test) proposed by Choi (2001). PS also presented a truncated version of the test in order to avoid undue influences of extreme outcomes that could emerge in the case of small T. The simple average of cross-sectionally augmented IPS test and its truncated version are also proposed:

$$CIPS(N, T) = N^{-1} \sum_{i=1}^N t_i(N, T) \quad (12)$$

and

$$CIPS^*(N, T) = N^{-1} \sum_{i=1}^N t_i^*(N, T) \quad (13)$$

where $t_i(N, T)$ and $t_i^*(N, T)$ are the cross-sectionally augmented Dickey-Fuller statistic for the i -th cross section unit and the truncated version respectively given by the t-ratio of the coefficient of $y_{i,t-1}$ in the CADF regression:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i y_{t-1} + d_i \Delta y_t + e_{it} \quad (14)$$

3.2 Panel cointegration tests

Kao (1999) proposed an Augmented Dickey-Fuller (ADF) panel cointegration test in which cointegrating vectors are assumed to be homogeneous. Let \hat{e}_{it} be the estimated residual from the following regression:

$$y_{it} = \alpha_i + \beta x_{it} + e_{it} \quad (15)$$

The ADF test is applied to the estimated residual:

$$\hat{e}_{it} = \gamma \hat{e}_{i,t-1} + \sum_{j=1}^p J_j \Delta \hat{e}_{i,t-j} + v_{i,tp} \quad (16)$$

where p is chosen so that the residual $v_{i,tp}$ are serially uncorrelated. The ADF test statistic is the usual t-statistic of $\rho = 1$ in the previous equation.

With the null hypothesis of no cointegration, the ADF test statistics can be constructed as:

$$ADF = \frac{t_{ADF} + \left(\sqrt{6N} \hat{\sigma}_v / 2 \hat{\sigma}_{0v} \right)}{\sqrt{\left(\hat{\sigma}_{0v}^2 / 2 \hat{\sigma}_v^2 \right) + \left(10 \hat{\sigma}_{0v}^2 \right)}} \quad (17)$$

where $\hat{\sigma}_v^2 = \sum_{u\varepsilon} - \sum_{u\varepsilon} \sum_{\varepsilon}^{-1}$, $\hat{\sigma}_{0v}^2 = \Omega_u - \Omega_{u\varepsilon} \Omega_{\varepsilon}^{-1}$, Ω is the long run covariance matrix and t_{ADF} is the t-statistic in the ADF regression. Kao shows that the ADF test converges to a standard normal distribution $N(0,1)$.

At least, a panel co-integration test for the null hypothesis of no co-integration with cross-sectional dependence is applied. Westerlund (2004) proposed a non-parametric modified variance ratio test. He considers the following model:

$$y_{it} = z_t' \hat{\delta}_i + x_{it}' \hat{\beta}_i + \hat{e}_{it} \quad (18)$$

where z_t is the deterministic component. z_t may include a constant and linear time trend. The variance ratio test is applied to the residual of the previous regression equation. The residual \hat{e}_{it} are stationary when y_{it} and x_{it} are co-integrated. In other words, testing the null hypothesis of no co-integration is equivalent to testing the regression residuals for a unit root using the following auto-regression:

$$\hat{e}_{it} = \gamma \hat{e}_{i,t-1} + u_{it} \quad (19)$$

For the test statistic, the null hypothesis is formulated as: $H_0 : \gamma_i = 1$ for all i , against the alternative $H_1 : \gamma_i = \gamma < 1$ for all i ⁸. Now, define $\hat{E}_{it} = \sum_{j=1}^t \hat{e}_{ij}$, $\hat{R}_i \equiv \sum_{t=1}^t \hat{e}_{it}^2$, $\hat{E}_i = (\hat{E}_{i1}, \dots, \hat{E}_{iT})'$, $\hat{E} = (\hat{E}_1, \dots, \hat{E}_N)'$, $\hat{U}_i = (\hat{e}_{i1}, \dots, \hat{e}_{iT})'$ and $\hat{U} = (\hat{U}_1, \dots, \hat{U}_N)'$.

⁸ A rejection of the null hypothesis should therefore be taken as evidence in favour of co-integration for all individuals

The modified variance ratio statistic developed by Westerlund is:

$$VR_M \equiv tr\left(\hat{E}'\hat{E}(\hat{U}'\hat{U})^{-1}\right) \quad (20)$$

3.3 Panel estimation of the long-run relationship

Pedroni provided the between-dimension “group mean” DOLS and FMOLS estimators. The advantage of using the between estimators is that the form in which the data is pooled allows for greater flexibility in the presence of heterogeneity of the cointegrating vectors. The test statistics derived from the between-dimension estimators are constructed to test the null hypothesis $H_0: \beta_i = \beta_0$ for all i against the alternative $H_1: \beta_i \neq \beta_0$, so that the values for β_i are not constrained to be the same under the alternative hypothesis. Consider the following co-integrated system for a panel of $i = 1, 2, \dots, N$ members,

$$\begin{aligned} Y_{it} &= \alpha_i + \beta X_{it} + u_{it} \\ X_{it} &= X_{it-1} + \varepsilon_{it} \end{aligned} \quad (21)$$

where $Z_{it} = (Y_{it}, X_{it})' \square I(1)_{it}$ and $\xi_i = (u_{it}, \varepsilon_{it})' \square I(0)$, with long run covariance matrix $\Omega_i = L_i L_i'$ (L_i is a lower triangular decomposition of Ω_i). In this case, the variables are said to be cointegrated for each member of the panel, with cointegrating vector β . The terms α_i allow the cointegrating relationship to include member specific fixed effect. The covariance matrix can also be decomposed as $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$, where Ω_i^0 is the contemporaneous covariance and Γ_i' is a weighted sum of autocovariances. The Panel FMOLS estimator for the coefficient β is defined as follows:

$$\beta_{NT}^* = N^{-1} \left(\sum_{i=1}^N (X_{it} - \bar{X}_i)^2 \right)^{-1} \left(\sum_{i=1}^N (X_{it} - \bar{X}_i) Y_{it}^* - T \hat{\tau}_i \right) \quad (22)$$

where $Y_{it}^* = (Y_{it} - \bar{Y}_i) - \frac{\hat{L}_{21i}}{\hat{L}_{22i}} \Delta X_{it}$, $\hat{\tau}_i \equiv \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^0 - \frac{\hat{L}_{21i}}{\hat{L}_{22i}} (\hat{\Gamma}_{22i} + \hat{\Omega}_{22i}^0)$ and \hat{L}_i is a lower triangular decomposition of $\hat{\Omega}_i$ defined as follows:

$$\Omega_i = \begin{bmatrix} \Omega_{11i} & \Omega'_{21i} \\ \Omega_{21i} & \Omega_{22i} \end{bmatrix}$$

For the panel DOLS estimation, the cointegration equation (21) is augmented as follows:

$$Y_{it} = \alpha_i + \beta X_{it} + \sum_{k=-K_i}^{K_i} \gamma_{ik} \Delta X_{it-k} + u_{it}^* \quad (23)$$

and the estimated coefficient β is given by:

$$\hat{\beta}_{GD}^* = N^{-1} \left(\sum_{i=1}^N Z_{it} Z_{it}' \right)^{-1} \left(\sum_{i=1}^N Z_{it} Y_{it}^* \right) \quad (24)$$

where $Z_{it} = (X_{it} - \bar{X}_i, \Delta X_{it-k}, \dots, \Delta X_{it+k})$ is $2(K+1) \times 1$ vector of regressors.

MS assume the hypothesis that the cointegrating vector is homogenous across individuals, but they allow for individual heterogeneity through disparate short-run dynamics, individual-specific fixed effects and individual-specific time trends. Their approach also allows for some degree of cross-sectional dependence through the presence of time-specific effects. The panel estimator for the fixed effect model is β_{NT} , where

$$(\beta_{NT} - \beta) = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{q}_{it}' \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{u}_{it} \right] \quad (25)$$

When individual-specific fixed effects and heterogeneous time trends are included in the model, the panel DOLS estimator is:

$$\beta_{NT} = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{q}_{it}' \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{y}_{it} \right] \quad (26)$$

The panel DOLS estimator with common time dummies in the model is⁹:

$$\underline{\gamma}_{NT} = \left[\sum_{i=1}^N \sum_{t=1}^T \underline{x}_{it}^{\perp*} \underline{x}_{it}^{\perp*0} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \underline{x}_{it}^{\perp*} \underline{y}_{it}^{\perp*} \right] \quad (27)$$

4. Data and empirical results

In our empirical analysis, we use a panel of Italian regions over the period 1970-1998. Annual data on value added and labor units in the industrial sector are taken from the Prometeia Regional Accounting data-set. The data for the stock of private capital in the industrial sector over the period 1970-1994 are provided by Paci and Pusceddu from CRENOS (University of Cagliari). Paci and Pusceddu (2000), as well as Gleed and Rees (1979), obtained the regional stocks of capital by distributing across regions the national stock of capital¹⁰ through two indicator variables, namely the regional share of gross investments (given a weight of 0.75) and the regional share of labour units (given a weight of 0.25). Following the same procedure, the time series of regional physical capital has been extended until 1998¹¹. Value added and stock of capital are measured at 1995 constant prices.

As mentioned in Section 2, the technique suggested in Hall and Jones (1999) has been adopted in order to estimate human capital. Let L_{it} be the number of employees in region i at time t , and F_{it} and M_{it} be the female and male average number of years of education in region i at time t ¹². Then, labor augmented for human capital accumulation in region i at time t can be defined by:

$$L_{it} h_{it} = L_{it} e^{[\phi_F F_{it} + \phi_M M_{it}]} \quad (28)$$

⁹ For further details on PDOLS estimators see Appendix.

¹⁰ The data on the national stock of capital are provided by the National Institute of Statistics (ISTAT).

¹¹ In these circumstances there is clearly some collinearity between the capital and the labour input, and while we can regard with some confidence the sum of the input elasticities, not much weight should be given to size and significance of any of them in isolation (this is especially true for the stock of capital).

¹² F_{it} and M_{it} data are taken from Destefanis *et al.* (2004).

where ϕ_F and ϕ_M are the coefficients on education in the Mincer earning functions. To obtain L_{it} h_{it} , the coefficients estimated by Brunello *et al.* (1999) for Italy, are used¹³.

In tables 1-3 panel unit root test results are reported. Strong evidence of unit root processes for all variables is found. With regard to the value added, only the Choi test allows rejection of the null hypothesis of nonstationarity at the 5% significance level. Other tests show significant evidence in favor of a unit root process.

Concerning the stock of physical and human capital, the null hypothesis of nonstationarity cannot be rejected at the 5% significance level, except for MP tests. However, the results of the Moon and Perron test are more 'radical' since they do not test for the unit root in common factors. The rejection of the null hypothesis does not imply that non-stationarity is rejected for the idiosyncratic component of all regions, but that the null hypothesis is only rejected for a subgroup of regions. In addition, the rejection of the non-stationarity of the idiosyncratic component does not imply that the series is stationary, since the common factor may be non-stationary.

In table 4 results of the panel cointegration tests are reported. All tests show evidence of a cointegrating relationship between the three variables considered at the 5% level, meaning that the residuals in the equation (3) are stationary.

Given the evidence of stationarity of the residuals in equation (3), we proceed to estimate the long-run relationship. In table 5, Pedroni's DOLS and FMOLS estimates are reported. The signs of coefficients are consistent with economic theory and all t-statistics are significant at the 5% level. Common time dummies are included to control for cross-sectional dependence. Evidence of constant or even decreasing returns to scale (scale elasticities are 0.99 for DOLS and 0.76 for FMOLS) is found when common time effects are included in the model. Otherwise, the regional production function exhibits slightly increasing returns to scale (scale elasticities are 1.05 and 1.15 for DOLS and FMOLS, respectively). These findings are consistent with the New Endogenous Growth Theory that points out the existence of increasing returns to scale due to spillover effects. It makes sense that the evidence of increasing returns should disappear once one controls for spillovers through the common time dummies. Low coefficients on physical capital (ranging from 0.16 to 0.26) were expected given the characteristics of the data on physical capital stock.

¹³ The ϕ_F and ϕ_M coefficients are respectively equal to 0.077 and 0.062.

Tab. 1 Panel unit root tests. Variable: LNVA

A. Choi Panel test				B. Pesaran panel test		
	Pm	Z	L*	p*	CIPS	CIPS*
	3.066	-3.103	-2.979	1	-2.238	-2.238
	(0.001)	(0.00)	(0.001)		(0.035)	(0.035)
				2	-2.141	
					(0.075)	
				3	-1.910	
					(0.280)	
				4	-1.641	
					(0.635)	
C. Bai and Ng panel test				D. Moon and Perron panel test		
	Idiosyncratic shocks		Common Factor \hat{F}	\hat{r}	t_a*	t_a*B
\hat{r}	$Z_{\hat{\epsilon}}^c$	$P_{\hat{\epsilon}}^c$	$ADF_{\hat{F}}^c$			
1	-1.589	25.879	-0.787	2	-0.990	-1.237
(BIC ₃)	(0.943)	(0.959)	(0.801)		(0.161)	(0.108)
				\hat{r}	t_b*	t_b*B
				2	-1.083	-1.048
					(0.139)	(0.147)

- Notes:
- a) The PM test is the modified Fisher’s inverse chi-square test (Choi, 2001). The Z test is an inverse normal test. The L* test is a modified logit test. All statistics have a standard normal distribution under H_0 when T and N tend to infinity (Choi, 2004a).
 - b) CIPS is the mean of individual cross-sectionally augmented ADF statistics (ADF). CIPS* indicates the mean of truncated individual CADF statistics. The truncated statistics are reported only for one lag since they are always equal to not truncated one for higher lag lengths. p* denotes the nearest integer of the mean of the individual lag lengths in ADF tests.
 - c) for each variable, the number of common factor estimated (\hat{r}) is estimated by the BIC3 criterion (we use the BIC3 criterion because N and T don’t have so much difference in magnitude), with a maximum number of factor equal to 5. For idiosyncratic components $\hat{\epsilon}_i$, the pooled unit root statistic tests are reported. $P_{\hat{\epsilon}}^c$ is a fisher’s type statistic based on a p-valued of the individual ASF tests. Under the null hypothesis, $P_{\hat{\epsilon}}^c$ has a $\chi^2(2N)$ distribution where T tends to infinity and N is fixed. $Z_{\hat{\epsilon}}^c$ is the standardized Choi’s type test statistic. Under the null hypothesis, $Z_{\hat{\epsilon}}^c$ has a N(0,1) distribution. For the idiosyncratic components \hat{F}_i , two different cases must be distinguished: if $\hat{r}=1$, only the standard ADF t-statistic, $ADF_{\hat{F}}^c$ is reported. If $\hat{r}>1$ the estimated number \hat{r} of independent stochastic trends in the common factors is reported (columns 4 and 5).
 - d) t_a* and t_b* are the panel unit root test based on de-factored panel data and computed with a quadratic spectral kernel function.
 - e) t_a*B and t_b*B are computed with a Barlett kernel function.
 - f) P-values are in parenthesis.

Tab. 2 Panel unit root tests. Variable: LNK

A. Choi Panel test				B. Pesaran panel test		
	Pm	Z	L*	p*	CIPS	CIPS*
	1.812	1.588	2.153	1	-1.853	-1.853
	(0.350)	(0.944)	(0.984)	2	(0.370)	(0.370)
					-1.525	
					(0.805)	
				3	-1.704	
					(0.550)	
				4	-1.349	
					(0.915)	
C. Bai and Ng panel test				D. Moon and Perron panel test		
	Idiosyncratic shocks		Common Factor \hat{F}	\hat{r}	T_a*	t_a*B
\hat{r}	$Z_{\hat{e}}^c$	$P_{\hat{e}}^c$	$ADF_{\hat{F}}^c$	4	-11.383	-12.765
1	0.859	48.011	-2.534		(0.000)	(0.000)
(BIC ₃)	(0.185)	(0.180)	(0.120)			
				\hat{r}	t_b*	t_b*B
				4	-5.719	-6.260
					(0.000)	(0.000)

Notes: see Table 1.

Tab. 3 Panel unit root tests. Variable: LNLH

A. Choi Panel test				B. Pesaran panel test		
	Pm	Z	L*	p*	CIPS	CIPS*
	2.830	-2.426	-2.407	1	-1.532	-1.410
	(0.002)	(0.058)	(0.061)	2	(0.795)	(0.823)
					-1.391	
					(0.915)	
				3	-1.566	
					(0.725)	
				4	-1.092	
					(0.990)	
C. Bai and Ng panel test				D. Moon and Perron panel test		
	Idiosyncratic shocks		Common Factor \hat{F}	\hat{r}	t_a*	t_a*B
\hat{r}	$Z_{\hat{e}}^c$	$P_{\hat{e}}^c$	$ADF_{\hat{F}}^c$	4	-7.036	-7.031
2	-1.249	28.830			(0.000)	(0.000)
(BIC ₃)	(0.894)	(0.905)	-			
				\hat{r}	t_b*	t_b*B
				4	-3.893	-3.858
					(0.000)	(0.000)

Notes: see Table 1.

Tab. 4 Panel cointegration tests results

Variables	ADF (Kao)	WR_M ^a (Westerlund)
lnVA, lnK, lnLh	-2.601 (0.001)	17.461 (0.005)

Notes: a) All tests are used to test the null hypothesis of no cointegration.
b) For the ADF test, the lag order is set to one. Results are robust to different lag lengths. The WRM is developed under the assumption of cross-sectional dependence. t. The distribution depends on the number of regressors (2 in our case), the deterministic specification of the spurious regression (in our analysis only the constant is included) and the number of the cross-sectional units.
c) numbers in parenthesis are p-values.

Tab. 5 Estimation Results. Method: DOLS and FMOLS (Pedroni , 1996, 2000, 2001)

	DOLS	DOLS (common time dummies)	FMOLS	FMOLS (common time dummies)
lnK	0.26 [2.12*]	0.17 [3.21*]	0.26 [14.27*]	0.16 [4.18*]
lnLh	0.79 [4.56*]	0.82 [2.63*]	0.89 [16.75*]	0.60 [5.31*]

Notes: a) common time dummies are included to check for cross-sectional dependence.
b) numbers in brackets are the t-statistics.
c) *denotes significant at 5% level.

Tab. 6 ESTIMATION RESULTS. METHOD: PDOLS (Mark and Sul, 2003)

	PDOLS (individual effect)	PDOLS (individual and common time effect)	PDOLS (individual effect and heterogenous trends)	PDOLS (individual effect, heterogenous trends and common time effect)
lnK	0.20 [2.22*]	0.13 [2.18*]	0.10 [0.62]	0.09 [0.65]
lnLh	1.07 [4.54*]	1.11 [6.43*]	0.71 [3.10*]	0.67 [2.61*]

Notes: a) common time effect allows to check for cross-sectional dependence.
b) numbers in brackets are the t-statistics based on parametrically corrected standard errors.
c) *denotes significant at 5% level.

The PDOLS estimates are presented in Table 6. The signs of the coefficients are always consistent with economic theory. The coefficients on physical capital are again rather low (ranging from 0.09 to 0.20) and not significant in the estimation of the model with individual effects and heterogenous trends as well as in the estimation of the model with individual, common time effect and heterogenous trends (see columns 3 and 4). Given the way in which the data on physical capital are constructed, these findings must be carefully considered.

The values of the scale elasticities slightly diminish when common time effects are included in the regional production function: from 1.27 to 1.24 (see the first and the second columns) and from 0.81 to 0.76 (see the third and the fourth columns). A much bigger impact is found when individual time trends are included in the model: the scale elasticities decline from 1.27 to 0.81 in the model without common time effects and from 1.24 to 0.76 in the model with common time effects.

In a nutshell, the estimation results reported in Tables 5 - 6 suggest that the presence of increasing returns to scale on physical and human capital may be due to the omission of some relevant factors (such as common time effects and individual trends) from the production function. When these factors are included in the model, constant or even decreasing returns to scale are found.

5. CONCLUSIONS

Whether they are based on non-stationary panel data techniques or not, aggregate production functions estimated on macro panel data for countries usually assume the hypothesis of cross-section independence. However this assumption is too strong, especially for regional data. Co-movements of economic variables between one region and another should be expected because of spillover effects, and empirical analysis should take this into account. In this paper, we exploit the time length of our panel dataset (1970-98) by using non-stationary panel methods explicitly allowing for a common time effect in order to take into account cross-regional dependence.

In providing estimates for a regional production function for the industrial sector across Italian regions, unit root properties of the panel dataset are firstly investigated through newly developed tests for cross-section dependence. After having ascertained the existence of a cointegrating relationship between value

added, human capital-augmented labor and physical capital, the long run relationship between the variables of interest is estimated through new procedures that allow for some degree of cross-section dependence.

These panel methods, which also allow for heterogeneity across regions, provide strong evidence in favour of a cointegrating relationship between regional value added, physical capital and human capital-augmented labour. When common time effects and individual trends are included in the model, the regional production function tends to be characterized by constant or even decreasing returns to scale. Otherwise, the production function exhibits slightly increasing returns to scale in particular with the Pedroni's estimator, in line with the new growth theories. Thus, we are more confident on Pedroni's results rather than Mark and Sul results, also because the Pedroni's group-mean panel DOLS estimator used in this analysis exhibits much less size distortion relative to the within-dimension panel DOLS estimators (see Pedroni, 2001).

A further step in our research agenda could be the adoption of recently developed estimators that model cross-section dependence using a common factor structure (Westerlund, 2005).

APPENDIX

A. Bai and Ng panel unit root test

Consider the following model with individual effect and without time trend:

$$y_{it} = \alpha_i + \lambda_i' F_t + e_{it} \quad (\text{A.1})$$

where F_t is a $r \times 1$ vector of common factors and λ_i is a vector of factor loadings¹⁴. Among the r common factors, we allow r_0 and r_1 to be stochastic common trends with $r_0 + r_1 = r$. The corresponding model in first difference is:

$$\Delta y_{it} = \lambda_i' F_t + z_{it} \quad (\text{A.2})$$

where $z_{it} = \Delta e_{it}$ and $f_t = \Delta F_t$ with $E(f_t) = 0$. Applying the principal-components approach to Δy_{it} yields r estimated factors \hat{f}_t , the associated loadings $\hat{\lambda}_i$, and the estimated residuals, $z_{it} = y_{it} - \hat{\lambda}_i' \hat{f}_t$.

If we define:

$$\hat{e}_{it} = \sum_{s=2}^t \hat{z}_{is}$$

$$\hat{F}_t = \sum_{s=2}^t \hat{z}_{ts}, \text{ an } r \times 1 \text{ vector, for } t = 2, \dots, T,$$

then we have:

1. Let $ADF_{\hat{e}}^c(i)$ be the t statistics for testing $d_{i0} = 0$ in the univariate augmented autoregression (with no deterministic terms):

$$\Delta \hat{e}_{it} = d_{i0} \hat{e}_{it-1} + d_{i1} \Delta \hat{e}_{it-1} + \dots + d_{ip} \Delta \hat{e}_{it-p} + error \quad (\text{A.3})$$

2. If $r = 1$, let $ADF_{\hat{F}}^c$ be the t statistics for testing $\delta_{i0} = 0$ in the univariate augmented autoregression (with an intercept):

$$\Delta \hat{F}_t = c + \delta_{i0} \hat{F}_{t-1} + \delta_{i1} \Delta \hat{F}_{t-1} + \dots + \delta_{ip} \Delta \hat{F}_{t-p} + error \quad (\text{A.4})$$

¹⁴ Specifically, the idiosyncratic error follows this process: $(1 - \rho_i L)e_{it} = D_i(L)\epsilon_{it}$.

3. If $r > 1$, demean \hat{F}_t and denote $\hat{F}_t^c = \hat{F}_t - \bar{\hat{F}}$, where $\bar{\hat{F}} = (T-1)^{-1} \sum_{t=2}^T \hat{F}_t$. Start with $m = r$;

A. $\hat{\beta}_\perp$ denotes the m eigenvectors associated with the m largest eigenvalues of $T^{-2} \sum_{t=2}^T \hat{F}_t^c \hat{F}_t^{c'}$ and $\hat{Y}_t^c = \hat{\beta}_\perp' \hat{F}_t^c$. Two different statistics may be considered:

B.I Let $K(j) = 1 - j/(j+1)$, $j = 0, 1, \dots, J$:

i) Let $\hat{\xi}_t^c$ be the residuals from estimating a first-order VAR in \hat{Y}_t^c . In addition, let

$$\hat{\Sigma}_1^c = \sum_{j=1}^J K(j) \left(T^{-1} \sum_{t=2}^T \hat{\xi}_{t-j}^c \hat{\xi}_t^{c'} \right)$$

ii) Let $v_c^c(m)$ be the smallest eigenvalue of

$$\Phi_c^c(m) = 0.5 \left[\sum_{t=2}^T (\hat{Y}_t^c \hat{Y}_{t-1}^{c'} + \hat{Y}_{t-1}^c \hat{Y}_t^{c'}) - T(\hat{\Sigma}_1^c + \hat{\Sigma}_1^c) \right] \left(\sum_{t=2}^T \hat{Y}_t^c \hat{Y}_{t-1}^{c'} \right)^{-1} \quad (\text{A.5})$$

iii) Define $MQ_c^c(m) = T [\hat{v}_c^c(m) - 1]$.

B.II For p fixed that does not depend on N and T

i) Estimate a VAR of order p in $\Delta \hat{Y}_t^c$ to get $\hat{\Pi}(L) = I_m - \hat{\Pi}_1 L - \dots - \hat{\Pi}_p L^p$ and filter \hat{Y}_t^c by $\hat{\Pi}(L)$, we have: $\hat{y}_t^c = \hat{\Pi}(L) \hat{Y}_t^c$.

ii) Let $\hat{v}_f^c(m)$ be the smallest eigenvalue of :

$$\Phi_f^c(m) = 0.5 \left[\sum_{t=2}^T (\hat{y}_t^c \hat{y}_{t-1}^{c'} + \hat{y}_{t-1}^c \hat{y}_t^{c'}) \right] \left(\sum_{t=2}^T \hat{y}_t^c \hat{y}_{t-1}^{c'} \right)^{-1} \quad (\text{A.6})$$

iii) Define the statistic $MQ_f^c(m) = T [\hat{v}_f^c(m) - 1]$

C. If $H_0 : r_1 = m$ is rejected, set $m = m - 1$ and return to step A. Otherwise, $\hat{r}_1 = m$ and stop.

B. Moon and Perron panel unit root test

The simple dynamic model provided by MP consists in the following equations:

$$\begin{aligned} y_{it} &= \alpha_i + y_{it}^0 \\ y_{it}^0 &= \rho_i y_{it-1}^0 + \varepsilon_{it}, \end{aligned} \quad (\text{B.1})$$

where $y_{it}^0 = 0$ for all i ¹⁵.

To model the cross-correlation, BM assume that the error term ε_{it} follows a factor model:

$$\varepsilon_{it} = \beta_i^{0t} f_t^0 + e_{it} \quad (\text{B.2})$$

where f_t^0 are K -vectors of unobservable random factor, β_i^0 are non-random factor loading coefficient vectors (also K -vectors), e_{it} are idiosyncratic shocks, and the number of factor K is possibly unknown.

Under the null hypothesis of $\rho_i = 1$ for all $i=1,2,\dots,N$, y_{it} is influenced by two components: the integrated factor $\sum_{s=1}^T f_s^0$ and the idiosyncratic errors

$\sum_{s=1}^T e_s$. With respect to the BNG test, the MP test is based only on the estimated idiosyncratic component. MP treat the factors as a nuisance parameter and propose to pool de-factored data. MP suggest removing cross-sectional dependence in the model (B.1-B.2) by multiplying the observed matrix Y of the dimension $(T \times N)$ by the projection matrix Q_B and compute the unbiased pooled autoregressive estimator as:

$$\rho_{pool}^+ = \frac{\text{tr}(Y_{-1} Q_B Y' - NT \lambda_e^N)}{\text{tr}(Y_{-1} Q_B Y_{-1}')} \quad (\text{B.3})$$

where Y_{-1} is the matrix of the lagged observed data, $\text{tr}(\cdot)$ is the trace operator and λ_e^N is the cross-sectional average of the one-sided long run variance of the

¹⁵ MP also consider a model with incidental trend: $y_{it} = \alpha_{ki}' g_{kt} + y_{it}^0$, where $g_{0t} = 1$ and $g_{1t} = (1, t)'$.

idiosyncratic errors e_{it} . The vector of factor loading $\hat{\beta}$ and the projection matrix Q_B are obtained by estimating the principal component of $\hat{e}'\hat{e} = (Y - \hat{\rho}_{pool}Y_{-1})'(Y - \hat{\rho}_{pool}Y_{-1})$, where $\hat{\rho}_{pool}$ is the OLS pooled autoregressive estimate.

C. Mark and Sul estimation procedure

Mark and SUL start from the Kao and Chang approach by assuming the hypothesis that the cointegrating vector is homogenous across individuals, but they allow for individual heterogeneity through disparate short-run dynamics, individual-specific fixed effect and individual-specific time trends. In addition, a limited degree of cross-sectional dependence through the presence of time-specific effects is considered. Consider the following model:

$$\begin{aligned} y_{it} &= \alpha_i + \lambda_i t + \mathcal{G}_i + \underline{\gamma}' \underline{x}_{it} + u_{it}^\dagger \\ \Delta \underline{x}_{it} &= \underline{v}_{it} \end{aligned} \quad (C.1)$$

where $(1, -\underline{\gamma}')$ is the cointegrating vector between y_{it} and \underline{x}_{it} which is identical across individuals.

The equilibrium error $y_{it} - \underline{\gamma}' \underline{x}_{it}$ may include an individual-specific effect α_i , an individual-specific linear trend $\lambda_i t$, and a common time-specific factor \mathcal{G}_i . The remaining idiosyncratic error u_{it}^\dagger is independent across i but possibly dependent across t . An alternative representation of the previous equation allows \underline{x}_{it} to have an individual-specific vector of drift terms and for the trend in the same equation to be induced by this drift. Mark and Sul consider the panel DOLS estimator of the vector of slope coefficients $\underline{\gamma}$. When the individual-specific constant ($\lambda_i = 0$, $\mathcal{G}_i = 0$) is included in the regression (C.1), we have:

$$y_{it} = \alpha_i + \underline{\gamma}' \underline{x}_{it} + u_{it}^\dagger \quad (C.2)$$

MS assume that u_{it}^\dagger is correlated with at most p_i leads and lags of $\underline{v}_{it} = \Delta \underline{x}_{it}$. In order to control for endogeneity problems, MS choose to project u_{it}^\dagger onto these p_i leads and lags:

$$u_{it}^\dagger = \sum_{s=-p_i}^{p_i} \underline{\delta}_{i,s}' v_{it-s} + u_{it} = \sum_{s=-p_i}^{p_i} \underline{\delta}_{i,s}' \Delta x_{it-s} + u_{it} = \underline{\delta}_i' z_{it} + u_{it} \quad (C.3)$$

where $\underline{\delta}_{i,s}$ is a $k \times 1$ vector of projection coefficients, $\underline{\delta}_i = (\underline{\delta}_{i,-p}, \dots, \underline{\delta}_{i,0}, \dots, \underline{\delta}_{i,p_i})'$ is a $(2p_i + 1)k$ -dimensional vector and $z_{it} = (\Delta x_{it-p_i}, \dots, \Delta x_{it}, \Delta x_{it+p_i})'$ is $(2p_i + 1)k$ -vector of leads and lags of the first difference of the variables x_{it} . By substituting the projection representation for u_{it}^\dagger in the equation (C.3) into the equation (C.2), we have:

$$y_{it} = \alpha_i + \underline{\gamma}' x_{it} + \underline{\delta}_i' z_{it} + u_{it} \quad (C.4)$$

The projection defines the new covariance stationary process, $\underline{w}_{it} = (u_{it}, v_{it})'$ where for each i ,

$$\underline{w}_{it} = \Psi_i(L) \underline{\varepsilon}_{it}, \quad \Psi_i(L) = \begin{bmatrix} \Psi_{uu,i}(L) & \underline{0}' \\ \underline{0} & \Psi_{vv,i}(L) \end{bmatrix},$$

and \underline{w}_{it} satisfies the functional central limit theorem

$$\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} \underline{w}_{it} \xrightarrow{D} \underline{B}_i = \Psi_i(1) \underline{W}_i$$

where $\underline{B}_i = (B_{ui}, B_{vi})'$, B_{ui} and B_{vi} are independent, and

$$\Omega_i = E[\underline{B}_i(1) \underline{B}_i(1)'] = \begin{bmatrix} \Psi_{uu,i}(1)^2 & \underline{0}' \\ \underline{0} & \Psi_{vv,i}(1) \Psi_{vv,i}(1)' \end{bmatrix} = \begin{bmatrix} \Omega_{uu,i} & \underline{0}' \\ \underline{0} & \Omega_{vv,i} \end{bmatrix}$$

If we take the time-series average of the equation (C.4), we have

$$\frac{1}{T} \sum_{t=1}^T y_{it} = \alpha_i + \underline{\gamma}' \frac{1}{T} \sum_{t=1}^T x_{it} + \underline{\delta}_i' \frac{1}{T} \sum_{t=1}^T z_{it} + \frac{1}{T} \sum_{t=1}^T u_{it} \quad (C.5)$$

By subtracting the previous equation from the equation (C.4), we obtain:

$$\tilde{y}_{it} = \underline{\gamma}' \tilde{x}_{it} + \underline{\delta}_i' \tilde{z}_{it} + \tilde{u}_{it} \quad (C.6)$$

where a “tilde” denotes the deviation of an observation from its time series average,

$$\tilde{y}_{it} = y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it}$$

$$\tilde{x}_{it} = x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it}$$

$$\tilde{z}_{it} = z_{it} - \frac{1}{T} \sum_{t=1}^T z_{it}$$

$$\tilde{u}_{it} = u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}$$

To solve the estimation problem, let \tilde{q}_{it} is the $2k \left(1 + \sum_{i=1}^N p_i\right)$ dimensional vector of which the first k elements are \tilde{x}_{it} , elements $k \left(1 + \sum_{j=1}^{i-1} (2p_j + 1)\right) + 1$ to $k \left(1 + \sum_{j=1}^i (2p_j + 1)\right)$ are \tilde{z}_{it} and 0s elsewhere.

In other words,

$$\tilde{q}_{1t} = (\tilde{x}_{1t} \quad \tilde{z}'_{1t} \quad \underline{0}' \quad \dots \quad \underline{0}')'$$

$$\tilde{q}_{2t} = (\tilde{x}_{2t} \quad \underline{0}' \quad \tilde{z}'_{2t} \quad \dots \quad \underline{0}')'$$

⋮

$$\tilde{q}_{Nt} = (\tilde{x}_{Nt} \quad \underline{0}' \quad \underline{0}' \quad \dots \quad \tilde{z}'_{Nt})'$$

Let the grand coefficient vector be $\underline{\beta} = (\underline{\gamma}', \delta'_1, \dots, \delta'_N)'$ and the compact form of the regression $\tilde{y}_{it} = \underline{\beta}' \tilde{q}_{it} + \tilde{u}_{it}$. The panel DOLS estimator for the fixed effect model is $\underline{\beta}_{NT}$, where

$$(\underline{\beta}_{NT} - \underline{\beta}) = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{q}'_{it} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{u}_{it} \right] \quad (\text{C.7})$$

When we consider both individual effects and heterogeneous time trends in the specification of the model and substitute the projection representation for the equilibrium error,

$$u_{it}^\dagger = \sum_{s=-p_i}^{p_i} \underline{\delta}'_{i,s} v_{it-s} + u_{it} = \sum_{s=-p_i}^{p_i} \underline{\delta}'_{i,s} \Delta x_{it-s} + u_{it} = \underline{\delta}'_i z_{it} + u_{it} \quad (\text{C.8})$$

into equation (C.2), we have:

$$\tilde{y}_{it} = \alpha_i + \lambda_i t + \underline{\gamma}' \tilde{x}_{it} + \underline{\delta}'_i \tilde{z}_{it} + \tilde{u}_{it} \quad (\text{C.9})$$

If we take the time series average of the previous equation, we obtain:

$$\frac{1}{T} \sum_{t=1}^T y_{it} = \alpha_i + \lambda_i \left(\frac{t+1}{2} \right) + \underline{\gamma}' \frac{1}{T} \sum_{t=1}^T x_{it} + \underline{\delta}'_i \frac{1}{T} \sum_{t=1}^T z_{it} + \frac{1}{T} \sum_{t=1}^T u_{it} \quad (\text{C.10})$$

where $\frac{1}{T} \sum_{t=1}^T t = \left(\frac{t+1}{2} \right)$.

By subtracting the (C.10) equation from the equation (C.9), we obtain :

$$\tilde{y}_{it} = \lambda_i \tilde{t} + \underline{\gamma}' \tilde{x}_{it} + \underline{\delta}'_i \tilde{z}_{it} + \tilde{u}_{it} \quad (\text{C.11})$$

where

$$\tilde{y}_{it} = y_{it} - \frac{1}{T} \sum_{t=1}^T y_{it}$$

$$\tilde{x}_{it} = x_{it} - \frac{1}{T} \sum_{t=1}^T x_{it}$$

$$\tilde{z}_{it} = z_{it} - \frac{1}{T} \sum_{t=1}^T z_{it}$$

$$\tilde{u}_{it} = u_{it} - \frac{1}{T} \sum_{t=1}^T u_{it}$$

$$\tilde{t} = t - \frac{T+1}{2}$$

To set up the panel DOLS estimator, let $\underline{\lambda}_N = (\lambda_1, \lambda_2, \dots, \lambda_N)'$, $\underline{\beta} = (\underline{\lambda}', \underline{\lambda}'_N, \delta'_1, \dots, \delta'_N)'$ and :

$$\begin{aligned}\underline{\lambda}_N &= (\lambda_1, \lambda_2, \dots, \lambda_N)', \quad \underline{\beta} = (\underline{\gamma}', \underline{\lambda}'_N \delta'_1, \dots, \delta'_N)', \\ \tilde{q}'_{1t} &= (\tilde{x}_{1t} \quad \tilde{t} \quad 0 \quad \dots \quad 0 \quad \tilde{z}'_{1t} \quad \underline{0}' \quad \dots \quad \underline{0}'), \\ \tilde{q}'_{2t} &= (\tilde{x}_{2t} \quad 0 \quad \tilde{t} \quad \dots \quad 0 \quad \underline{0}' \quad \tilde{z}'_{2t} \quad \dots \quad \underline{0}'), \\ &\vdots \\ \tilde{q}'_{Nt} &= (\tilde{x}_{Nt} \quad 0 \quad 0 \quad \dots \quad \tilde{t} \quad \underline{0}' \quad \underline{0}' \quad \dots \quad \tilde{z}'_{Nt})'\end{aligned}$$

The panel DOLS estimator of β is:

$$\underline{\beta}_{NT} = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{q}'_{it} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{q}_{it} \tilde{y}_{it} \right] \quad (\text{C.12})$$

When we introduce the common time effect in order to allow a limited form of cross-sectional dependence and substitute the projection representation for u_{it}^\dagger in the equation $y_{it} = \alpha_i + \underline{\gamma}' \underline{x}_{it} + u_{it}^\dagger$, we have :

$$\tilde{y}_{it} = \alpha_i + \lambda_i t + \mathcal{G}_i + \underline{\gamma}' \tilde{x}_{it} + \delta'_i \tilde{z}_{it} + \tilde{u}_{it} \quad (\text{C.13})$$

Controlling for the common time effect requires an analysis of the cross-sectional average of the observations. Because MS admit heterogeneity in the projection coefficients δ_i across i , the resulting cross-sectional averages will involve sums such as $\sum_{j=1}^N \delta'_j \underline{z}_{jt}$ which complicates estimation of the δ_i coefficients. The estimation problem can be simplified by proceeding sequentially and addressing the endogeneity correction separately from co-integration vector estimation.

To this end, let $y_{it}^{\dagger\dagger}$ be the error from projecting each element of y_{it} onto $\underline{n}_{it} = (1, t, \underline{z}'_{it})$ and $\underline{x}_{it}^{\dagger\dagger} = \underline{x}_{it} - \Phi_i \underline{n}_{it}$ be the vector of projection errors from projecting each element of \underline{x}_{it} onto \underline{n}_{it} , where Φ_i is a $(k+2) \times p_i$ matrix of

projection coefficients. By substituting the projection representations for y_{it} and x_{it} into equation (C.13), we have:

$$\tilde{y}_{it}^{\dagger\dagger} = \underline{\gamma}' \underline{x}_{it}^{\dagger\dagger} + \mathcal{G}_t + u_{it} \quad (\text{C.14})$$

To estimate the parameter $\underline{\gamma}$ in the equation (C.13), equation (C.14) is used. Taking the cross-sectional average of equation (C.14), we have:

$$\frac{1}{N} \sum_{i=1}^N y_{it}^{\dagger\dagger} = \underline{\gamma}' \left[\frac{1}{N} \sum_{i=1}^N x_{it}^{\dagger\dagger} \right] + \mathcal{G}_t + \frac{1}{N} \sum_{j=1}^N u_{jt} \quad (\text{C.15})$$

Subtracting equation (C.15) from equation (C.14) eliminates the common time effect giving:

$$\tilde{y}_{it}^{\dagger\dagger} = \underline{\gamma}' \underline{x}_{it}^{\dagger\dagger*} + \mathcal{G}_t + u_{it}^* \quad (\text{C.16})$$

where the 'asterisk' indicates the deviation of an observation from its cross-sectional average. The panel DOLS estimator of $\underline{\gamma}$ is:

$$\underline{\gamma}_{NT} = \left[\sum_{i=1}^N \sum_{t=1}^T \underline{x}_{it}^{\dagger\dagger*} \underline{x}_{it}^{\dagger\dagger*0} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \underline{x}_{it}^{\dagger\dagger*} \underline{y}_{it}^{\dagger\dagger*} \right] \quad (\text{C.17})$$

where

$$\begin{aligned} y_{it}^{\dagger\dagger*} &= y_{it}^{\dagger\dagger} - \frac{1}{N} \sum_{j=1}^N y_{jt}^{\dagger\dagger} \\ \underline{x}_{it}^{\dagger\dagger*} &= \underline{x}_{it}^{\dagger\dagger} - \frac{1}{N} \sum_{j=1}^N \underline{x}_{jt}^{\dagger\dagger} \\ u_{it}^* &= u_{it} - \frac{1}{N} \sum_{j=1}^N u_{jt} \end{aligned}$$

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