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

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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 co-integrating relationship between value added, physical and human capital variables is investigated. The Dynamic OLS (DOLS) and Fully modified (FMOLS) estimators developed by Pedroni (1996[35], 2000[36], 2001[37]) and the Panel Dynamic OLS (PDOLS) estimator proposed by Mark and Sul (2003[31]) 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[2]; Holtz-Eakin, 1994[16]; Islam, 1995[20]; Garcia-Mila, McGuire and Porter, 1996[12]). More recent works consider non-stationary panel data techniques (e.g. McCoskey and Kao, 1999[29]; 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 data set are properly investigated by applying newly developed tests for cross-sectionally dependent panels. Second, the existence of a co-integrating 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 considered.[1] 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 organized 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 (1996, 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):

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

where Y_{it} 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 component into the model. Specifically, we define a simple knowledge production function for region i at time t as follows:

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

where A_{it} denotes the level of technology in region i at time t, γ_i is a region-specific constant which captures the intrinsic efficiency in technology production, the δ_{it} component catches the growth path of region-specific efficiency in producing technology, θ_t captures the worldwide (or countrywide) knowledge accumulation and ε_{it} 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 dependence.[2] As usual, labor $L_{i,t}$ is assumed to be homogenous within a region and h_{it} is a transformation of $E_{i,t}$ that measures the education level of each labor unit in terms of years of schooling. Thus, human capital-augmented labor 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 labor unit with E years of schooling relative to one with no education ($\phi(E) = 0$). 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:

$$lnY_{i,t} = \gamma_i + \delta_i t + \theta_t + \alpha lnK_{i,t} + \beta lnL_{i,t}h_{i,t} + \varepsilon_{i,t} \tag{3}$$

[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 to not 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

The panel model includes a regional-specific effect γ_i, a regional-specific liner 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[27]) 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[15] and Aiello and Scoppa, 2000[1]). 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 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 emphasized by Marrocu et al. (2000[28]), 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 data set, 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 captured.[3].

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[23], 1993[24]; Levin, Lin and Chu, 2002[25]; Im Pesaran and Shin, 1997[18], 2003[19]; Choi, 2001[7]; Maddala and Wu, 1999[26]) correlations across units constitute nuisance parameters. The cross-sectional independence hypothesis is rather restrictive and somewhat unrealistic in the majority of macroeconomic applications of unit root tests (Phillips and Sul, 2003[40]; O'Connel, 1998[32]), 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[5] and 2003[6]; Choi, 2004[8]; Bai and Ng, 2003[3]; Moon and Perron, 2004[30]; Pesaran, 2005[39]) aims at exploiting these co-movements in order to define new test statistics.[4] In this paper four cross-sectional dependent panel unit root tests are performed: Choi (2004, 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[21]), Panel-t test statistic (Pedroni, 1995[34], 2004[38]), the CUSUM test (Westerlund, 2005a[44]) and the WR_M test (Westerlund, 2004[43]) are applied. In Kao (1999) the hypothesis of homogeneity of the cointegrating vector among individual members of the panel is assumed while in Pedroni's approach this hypothesis is released and heterogeneity is considered. Westerlund (2005a) proposes a simple residual-based panel CUSUM test of the null hypothesis of cointegration. The test has a limiting normal distribution that is free of nuisance parameters, it is robust to heteroskedasticity and it allows for mixtures of cointegrated and spurious alternatives. Unlike previous panel cointegration tests, the W_{RM} test allows for cross-sectional dependence. Finally, the long run relationship is estimated by using the DOLS and FMOLS

[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

[4]A macroeconomics application is, e.g, in Hurlin (2004[17])

[5]Gutierrez (2003[14]) 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. Gutierez shows that all tests lack power when a deterministic trend is included in the data generating process

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[10]) GLS-based de-trending and the conventional cross-sectional demeaning panel data. The panel unit root tests developed by CH are:

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

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

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

where P_m test is a modification of Fisher (1932[11]) inverse chi-square, $\Phi(\cdot)$ is the standard normal cumulative distribution function and p_i indicates the asymptotic p-value of one the Dickey-Fuller-GLS test for region i.[6] For $T \longrightarrow \infty$ and $N \longrightarrow \infty$ one has that P_m, Z, and $L^* \Longrightarrow N(0,1)$.

BNG consider the factor model:

$$Y_{it} = D_{it} + \lambda_i' F_t + e_{it} \tag{7}$$

where D_{it} is a polynomial trend function, F_t is an $r \times 1$ vector of common factors, and λ_i ia vector of factor loading. 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 components $\hat{e}_{it}$ in a model with no

[6]The percentiles of the asymptotic p-values of the Dickey-Fuller-GLS tests are simulated by choi

deterministic trend:

$$\Delta e_{it} = \delta_{i,0}\hat{e}_{i,t-1} + \sum_{j=1}^{p} \delta_{i,j}\Delta\hat{e}_{i,t-j} + \mu_{i,t}. \tag{8}$$

Let $ADF^c_{\hat{e}}(i)$ be the ADF t-statistic for the i-th country. The asymptotic distribution of the $ADF^c_{\hat{e}}(i)$ 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 (2004) proposed pooled tests based on Fisher's type statistics defined as in Choi (2001) and Maddala and Wu (1999). Let $P^c_{\hat{e}}(i)$ be the p-value of the $ADF^c_{\hat{e}}(i)$, then

$$Z^c_{\hat{e}} = \frac{-2\sum_{i=1}^{N}\log P^c_{\hat{e}}(i) - 2N}{\sqrt{4N}} \longrightarrow N(0,1) \tag{9}$$

MP (2004) developed several unit root tests in which the cross-sectional units are correlated. To model the cross-sectional dependence, MP (2004) 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 but to which each individual reacts heterogeneously. In our analysis, we apply the following tests:

$$t^*_a = \frac{\sqrt{N}T(\hat{\rho}^+_{pool} - 1)}{\sqrt{\frac{2\hat{\phi}^4_e}{\omega^4_e}}} \tag{10}$$

$$t^*_b = \sqrt{N}T(\hat{\rho}^+_{pool} - 1)\sqrt{\frac{1}{NT^2}tr(Y_{-1}Q_B Y'_{-1})}(\frac{\hat{\omega^2_e}}{\phi^4_e}) \tag{11}$$

where $\hat{\rho}^+_{pool}$ is the bias-corrected pooled autoregressive estimated of ρ^+_{pool}, $\hat{\omega}^4_{\hat{e}}$ and $\hat{\phi}^4_{\hat{e}}$ are respectively the estimates of the cross sectional average of the long run variance of $\hat{e}_{it}$ and the cross sectional average of $\omega^4_{\hat{e},i}$.[7]

To deal with the problem of cross-sectional dependencies PS does not consider the deviations from the estimated common factor, but he proposed to augment 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 augumented ADF statistics (CADF). The individual CADF statistics may be used to build modified versions of the t-bar test developed by Im, Pesaran and Shin (2003), the inverse chi-square test (P test) developed by Maddala and Wu (1999) and the inverse normal test (Z test) proposed by Choi(2001). PS presented also a truncated version of the test in order to

[7] for details see Appendix

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:

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

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

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 OLS estimate of b_i $(\hat{b_i})$ in the CADF regression:

$$\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_{t-1} + e_{it}. \tag{14}$$

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:

$$y_{it} = \alpha_i + \beta x_{it} + e_{it} \tag{15}$$

The ADF test is applied to the estimated residual: where p is chosen so that the residual $\nu_{i,tp}$ are serially uncorrelated. The ADF test statistic is the usual t-statistic of in the previous equation. With the null hypothesis of no cointegration, the ADF test statistics can be constructed as:

$$ADF = \frac{t_{ADF} + (\frac{\sqrt{6N}\hat{\sigma}_\nu}{2\hat{\sigma}_{0\nu}})}{\sqrt{(\frac{\hat{\sigma}_{0\nu}^2}{2\hat{\sigma}_\nu^2}) + (10\hat{\sigma}_{0\nu}^2)}} \tag{16}$$

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

Pedroni (1995 and 2004) developed a method for testing the null hypothesis of no co-integration in dynamic panels with multiple regressors. The panel co-integration tests proposed allow the co-integrating vector to differ across members under the alternative hypothesis (heterogeneity). Imposing homogeneity of the co-integrating vectors in the regression would lead to reject the null hypothesis of no co-integration when the variables are actually co-integrated. To develop panel co-integration tests, Pedroni considered the following model:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + ... + \beta_{Mi} x_{Mi,t} + e_{it} \tag{17}$$

where T (t=1,....T) denotes the number of observations over time, N (i=,.....N) indicates the number of individuals in the panel and M (m=1,.....,M) refers to the number of regression variables. In the previous equation,α_i is the fixed effect parameter, $\delta_i t$ is the "time trends" parameter and $\beta_{1i}, \beta_{2i}, ...\beta_{Mi}$ are the slope coefficients which vary across individuals. In many applications,it could also be useful to include a set of common-time dummies in order to capture disturbances which may be shared across the individuals of the panel. Pedroni proposed seven different panel co-integration tests which are constructed using the residual of the co-integrating regression in the equation (17). Four tests are referred to as within dimension and three as the between-dimension. The first class of the panel tests is constructed by summing both the numerator and the denominator over the N dimension separately. The second class is constructed by first dividing the numerator by the denominator prior to summing over the N dimension. In our empirical analysis, the fourth parametric panel-t test is applied:

$$Z^*_{t_{T,N}} \equiv (\tilde{s}^{*2}_{N,T} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}^2_{11i} \hat{e}^2_{i,t-1})^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{i=1}^{T} \hat{L}^2_{11i} \hat{e}^*_{i,t-1} \Delta \hat{e}^*_{i,t} \tag{18}$$

where $\tilde{s}^{*2}_{N,T} \equiv \sum_{i=1}^{N} \tilde{s}^{*2}_i$ is the contemporaneous panel variance estimator, $\tilde{s}^{*2}_i$ is the standard contemporaneous variance of the residual from the ADF regression and L^2_{11i} is a nuisance parameter estimator that is used in Pedroni's tests and corresponds to the member specific long run conditional variance for the residuals. At least, a panel co-integration test for the null hypothesis of no co-integration with cross-sectional dependence is applied.

Westerlund (2005a) develops a simple residual-based panel CUSUM test of the null hypothesis of cointegration. The test has a limiting normal distribution that is free of nuisance parameters, it is robust to heteroskedasticity and it allows for mixtures of co-integrated and spurious alternatives. The null hypothesis in this paper is that all the individuals of the panel are co-integrated and the alternative is that a nonempty subset is not co-integrated. It's often argue that cointegration would be a more natural choice of null hypothesis in many empirical applications. Moreover, failure to reject the null of no cointegration could be caused not by the underline characteristic of the data, but rather then the low power of the test itself. Westerlund (2005a) consider the following model:

$$y_{it} = X^{'}_{it} = \delta i + u_{it} \tag{19}$$

where $X_{it} = (z^{'}_t)$ is a vector of right hand side variables and $\delta_i = (\gamma_i, \beta_i)^{'}$ is a conformable vector of parameters. The vector $x_{it} = x_{it-1} + \nu_{it}$ has dimension $K \times 1$ and contains the regressors, whereas z_t is a vector of deterministic component such that $z_t = \oslash$ in Model 1, $z_t = 1$ in Model 2 and $z_t = (1, t)$ in Model 3. The vectors γ_i and β_i are conformable with z_t and x_{it}, respectively. In each model, to enable general forms of temporal dependence within each cross-section, we assume that the error vector $w_{it} = (u_{it}, v_{it}^{'})^{'}$ satisfies the linear process conditions of Phillips and Solo (1992[41]). The null hypothesis is that all the individuals of the panel are cointegrated and the alternative is that a nonempty subset is not cointegrated. Formally, if $\frac{N_1}{N} \longrightarrow \infty$ as $N \longrightarrow \infty$ where N_1 denotes the number of individual processes u_{it}^{*} possessing a unit root and $\Psi \epsilon (0, 1)$, then we may formulate the null and alternative hypotheses as $H_0 : \Psi = 0$ against $H_1 : \Psi > 0$. This hypothesis allows for a nonzero subset of the processes u_{it} to be nonstation- ary under the alternative and it includes the full panel nonstationary alternative as a special case. Then, if y_{it} and x_{it} are co-integrated, the residual series $\hat{u}_{it}^{*}$ it should be stable around a fixed mean and its fluctuations should reflect only equilibrium errors. Conversely, if y_{it} and x_{it} are unrelated, then $\hat{u}_{it}^{*}$ becomes a unit root process. As a result,the fluctuations in $\hat{u}_{it}^{*}$ can be expected to be of a larger order magnitude than if y_{it} and x_{it} were co-integrated. This suggests that the null hypothesis of co-integration can be tested by looking at the fluctuation of $\hat{u}_{it}^{*}$. If $\hat{u}_{it}^{*}$ display very large fluctuation, we should reject the null hypothesis. To measure the fluctuation in $\hat{u}_{it}^{*}$, Westerlund (2005a) proposes the a panel CUSUM test statistic, which is the cross-sectional average of the univariate statistic of Xiao and Phillips (2001[?]) applied to each individual i. The statistic is defined as follows:

$$CS_{NT} \equiv \frac{1}{N} \sum_{i=1}^{N} (\underset{t=1,....T}{max} \frac{1}{\hat{\omega}_{i1.2} T^{1/2}} |S_{it}^{*}|) \tag{20}$$

where $S_{it}^{*} = \sum_{j=1}^{t} \hat{u}_{ij}^{*}$ and $\hat{\omega}_{i1.2}^{*} = \hat{\omega}_{i11} - \hat{\omega}_{i21}^{'} \hat{\Omega}_{i22}^{-1} \hat{\omega}_{i21}$ may be any consistent semiparametric kernel estimator of $\omega_{i1.2}^{*}$, which depends on the bandwidth parameter M. $\hat{\omega}_{i1.2}^{*}$ represents the long-run variance of u_{it}. The CUSUM statistics measures the magnitude of the residual variation from the regression of y_{it} on x_{it} against the magnitude of the estimated long-run conditional variance of u_{it} given v_{it}. If y_{it} and x_{it} are co-integrated, then the statistic should stabilize asymptotically. If not, then the increased residual variation will cause the statistic to diverge.

Westerlund (2004) proposed a non-parametric modified variance ratio test. He considers the following model:

$$y_{it} = z_t^{'} \hat{\delta}_i + x_{it}^{'} \hat{\beta}_i + \hat{e}_{it} \tag{21}$$

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 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:

$$\hat{e}_{it} = \gamma \hat{e}_{i,t-1} + \mu_{it} \tag{22}$$

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.

Now, let $\hat{E}_t = (\hat{E}_{i1}, ..., \hat{E}_{iT})$, $\hat{E} = (\hat{E}_1, ..., \hat{E}_N)$, $\hat{U}_i = (\hat{e}_{i1}, ..., \hat{e}_{iT})^{'}$ and $\hat{U} = (\hat{e}_1, ..., \hat{U}_N)^{'}$. The modified variance ratio statistic developed by Westerlund is:

$$VR_M \equiv tr(\hat{E}^{'}\hat{E}(\hat{U}^{'}\hat{U})^{-1}) \tag{23}$$

3.3 Panel estimation of the long-run relationship

PED 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 $i = 1, 2, .N$ members,

$$Y_{it} = \alpha_i + \beta X_{it} + \mu_{it} \tag{24}$$

$$X_{it} = X_{it-1} + \varepsilon_{it} \tag{25}$$

where $Z_{it} = (Y_{it}, X_{it}) \sim I(1)_{it}$ and $\xi_i = (\mu_{it}, \varepsilon_{it}) \sim I(0)$, with long run covariance matrix $\Omega_i = L_i L_i^{'}$ (L_i is a lower triangular decomposition ofΩ_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 is a weighted sum of autocovariances. The Panel FMOLS estimator for the coefficient β is defined as follows:

$$\beta^*_{NT} = N^{-1}(\sum_{i=1}^{N}(X_{it} - \bar{X}_i)^2((X_{it} - \bar{X}_i)Y^*_{it} - T\hat{\tau}_i) \tag{26}$$

where $Y^*_{it} = (Y_{it} - \bar{Y}_i) - \frac{\hat{L}_{21i}}{\hat{L}_{22i}}\Delta X_{it}, \hat{\tau}_i \equiv \hat{\Gamma}_{21i} + \hat{\Omega}^0_{21i} - \frac{\hat{L}_{21i}}{\hat{L}_{22i}}(\hat{\Gamma}_{22i} + \hat{\Omega}^0_{22i})$ and $\hat{L}_i$ is a lower triangular decomposition of $\hat{\Omega}_i$ defined as follows: $\Omega_i = \begin{pmatrix} \Omega_{11i} & \Omega^{'}_{21i} \\ \Omega_{21i} & \Omega_{22i} \end{pmatrix}$.

For the panel DOLS estimation, the cointegration equation (24) is augmented as follows:

$$Y_{it} = \alpha_i + \beta X_{it} + \sum_{k=-K_i}^{K_i} + \mu^*_{it} \tag{27}$$

and the estimated coefficient β is given by:

$$\hat{\beta}^*_{GD} = N^{-1}(\sum_{i=1}^{N} Z_{it}Z'_{it})^{-1}(\sum_{i=1}^{N} Z_{it}Y^*_{it}) \tag{28}$$

where $Z_{it} = (X_{it} - \bar{X}_i, \Delta X_{it-k}, ..., \Delta X_{it+k})$ 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

$$(\beta_{NT} - \beta) = [\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it}\tilde{\underline{q}}'_{it}]^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it}\tilde{\mu}'_{it}] \tag{29}$$

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

$$(\beta_{NT} - \beta) = [\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it}\tilde{\underline{q}}'_{it}]^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it}\tilde{y}'_{it}] \tag{30}$$

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

$$\gamma_{NT} = [\sum_{i=1}^{N}\sum_{t=1}^{T} \underline{x}^{\ddagger *}_{it}\underline{x}^{\ddagger * 0}_{it}]^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T} \underline{x}^{\ddagger *}_{it}y^{\ddagger *}_{it}] \tag{31}$$

In our empirical analysis all estimators are used.[8]

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[33]), as well as Gleed and Rees

[8]for details on these estimators see the Appendix

(1979[13]), obtained the regional stocks of capital by distributing across regions the national stock of capital 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).[9] Following the same procedure, the time series of regional physical capital has been extended until 1998.[10] 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.[11] Then, labor augmented for human capital accumulation in region i at time t can be defined by:

$$L_{it}h_{it}e^{[\phi_F F_{it}+\phi_M M_{it}]} \tag{32}$$

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[4]) for Italy, are used.[12] 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.

Table 1 about here.

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 sub-group 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.

Tables 2 and 3 about here.

In table 4 results of the panel cointegration tests are reported. All tests show evidence of a cointegrating relationship between the three variables

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

[10]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).

[11]F_{it} and M_{it} data are taken from Destefanis et al. (2004[9]).

[12]The ϕ_F and ϕ_F coefficients are respectively equal to 0.077 and 0.062

considered at the 5% level, meaning that the residuals in the equation (3) are stationary.

Table 4 about here.

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 disappears 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.

Table 5 about here.

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.

Table 6 about here.

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 spill-over effects, and empirical analysis should take this into account. In this paper, we exploit the time length of our panel data set (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 data set 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. This 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, 2005b[45]).

6 Appendix

6.1 Bai and NG panel unit root test

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

$$y_{it} = \alpha_i + \beta x_{it} + e_{it} \tag{33}$$

where F_t is a $r \times 1$ vector of common factors and λ_t is a vector of factor loadings.[13] Among the r common factors, we allow $r0$ and r_1 to be stochastic common trends with $r_0 + r_1 = r$. The corresponding model in first difference is:

$$\Delta y_{it} = \lambda_i^{'} + z_{it} \tag{35}$$

where $z_{it} = \Delta e_{it}$ and $f = \Delta F_{it}$ with $E(f_t) = 0$. Applying the principal-components approach to Δy_{it} yields r estimated factors $\widehat{f_t}$, the associated loadings $\widehat{\lambda}_t$, and the estimated residuals, $z_{it} = y_{it} - \hat{\lambda}_i^{'} \hat{f}_t$. Define for $t = 2....,T$

$\hat{e}_{it} = \sum_{s=2}^{t} \hat{z}_{it}$ (i=1,....N)

$\hat{F}_t = \sum_{s=2}^{t} \hat{z}_{it}$, an $r \times 1$ vector.

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):

$$\Delta \hat{e}_{it} = d_{i0} \hat{e}_{it-1} + d_{i1} \Delta \hat{e}_{it-1} + d_{ip} \Delta \hat{e}_{it-p} + error \tag{36}$$

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

$$\Delta \hat{F}_{it} = c + \delta_0 \hat{F}_{t-1} + \delta_1 \Delta \hat{e}_{t-1} + \delta_p \Delta \hat{F}_{it-p} + error \tag{37}$$

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

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

B.I: Let $K(j) = 1 - \frac{j}{(j+1)}$, $j = 0, 1, ...J$

i) Let $\hat{\xi}_t^c$ be the residuals from estimating a first-order VAR in $\hat{Y}_t^c$. In addition, let $\hat{\sum}_1^c = \sum_{j=1}^{J} K(j)(T^{-1} \sum_{t=2}^{T} \hat{\xi}_{t-j}^c \hat{\xi}_t^{c'})$

[13] Specifically, the idiosyncratic error follows this process:

$$(1 - \rho_i L) e_{it}) = D_i(L) \epsilon_{it}. \tag{34}$$

ii) Let v_c^M be the smallest eigenvalue of:

$$\Phi_c^c(m) = 0.5[\sum_{t=2}^{T}(\hat{Y}_t^c\hat{Y}_{t-1}^{c'} + \hat{Y}_{t-1}^c\hat{Y}_t^{c'}) - T(\hat{\Sigma}_1^c + \hat{\Sigma}_1^{c'})](\sum_{t=2}^{T}\hat{Y}_t^c\hat{Y}_{t-1}^{c'})^{-1} \quad (38)$$

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

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 $\hat{\prod}(L) = I_m - \hat{\prod}_1 L - .... - \hat{\prod}_p Lp$ and filter $\hat{Y}_t^c$ by $\hat{\prod}(L)$, we have: $\hat{y}_t^c = \hat{\prod}(L)\hat{Y}_t^c$

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

$$\Phi_c^f(m) = 0.5[\sum_{t=2}^{T}(\hat{y}_t^c\hat{y}_{t-1}^{c'} + \hat{y}_{t-1}^c\hat{y}_t^{c'})](\sum_{t=2}^{T}\hat{y}_t^c\hat{y}_{t-1}^{c'})^{-1} \quad (39)$$

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

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.

6.2 Moon and Perron panel unit root test

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

$$y_{it} = \alpha_i + y_{it}^0 \quad (40)$$

$$y_{it}^0 = \rho_i y_{it-1}^0 + \varepsilon_{it}, \quad (41)$$

where $y_{it}^0 = 0$ for all i.[14]To model the cross-correlation, BM assume that the error term follows a factor model:

$$\varepsilon_{it} = \beta_i^{0t} f_t^0 + e_{it}, \quad (42)$$

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 $i = 1, 2, .., N$, y_{it} is influenced by two components: the integrated factor $\sum_{s=1}^{T} f_t^0$ 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 $(40 - 41)$ by multiplying the observed matrix Y of the dimension $(N \times T)$ by the projection matrix Q_B and compute the unbiased pooled autoregressive estimator as:

$$\rho_{pool}^{+} = \frac{tr(Y_1 Q_B Y' - NT\lambda_e^N)}{tr(Y_{-1} Q_B Y_{-1}')} \quad (43)$$

[14]MP also consider a model with incidental trend

where N and T are the cross and time dimension respectively, Y_{-1} is the matrix of the lagged observed data, $tr(\cdot)$ is the trace operator and $\lambda_e^N$is the cross-sectional average of the one-sided long run variance of the 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.

6.3 Mark and Sul estimation procedure

Mark and SUL start from the Kao and Chang(2000[22]) 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:

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \underline{\gamma}' \underline{x}_{it} + u_{it}^{\dagger} \tag{44}$$

$$\Delta \underline{x}_{it} = \underline{\nu}_{it} \tag{45}$$

where $(1, -\underline{\gamma}')$ is the cointegrating vector between and which is identical across individuals. The equilibrium error may include an individual-specific effect α_i, an individual-specific linear trend $\lambda_i t$, and a common time-specific factor θ_t. The remaining idiosyncratic error 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 $(\lambda_t = 0, \theta_t = 0)$is included in the regression (44), we have:

$$y_{it} = \alpha_i + \underline{\gamma}' \underline{x}_{it} + u_{it}^{\dagger} \tag{46}$$

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

$$u_{it}^{\dagger} = \sum_{s=-p_i}^{i} \underline{\delta}_{i,s}' \underline{\nu}_{it-s} + u_{it} = \sum_{s=-p_i}^{p_i} \underline{\delta}_{i,s}' \Delta \underline{x}_{it-s} + u_{it} = \underline{\delta}_i' \underline{z}_{it} + u_{it} \tag{47}$$

where $\underline{\delta}_{i,s}$ is a $k \times 1$ vector of projection coefficients, $\underline{\delta}_i = (\underline{\delta}_{i,-p_i}, ..., \delta_{i,0}, ..., \delta_{i,p_i}')$ is a $(2p_i + 1)k$ dimensional vector and $z_{it} = (\Delta \underline{x}_{it-p_i}, ..., \Delta \underline{x}_{it-p_i}, ...\Delta \underline{x}_{it+p_i})$ is $(2p_i + 1)$ vector of leads and lags of the first difference of the variables $\underline{x}_{it}'$. By substituting the projection representation for in the equation (47) into the equation (46), we obtain:

$$y_{it} = \alpha_i + \underline{\gamma}' x_{it} + \underline{\delta}_i' \underline{z}_{it} + u_{it} \tag{48}$$

The projection defines the new covariance stationary process, $\underline{w}_{it} = (u_{it}, \nu_{it}^{'})^{'}$, where for each i: $\underline{w}_{it} = \Psi_i(L)\varepsilon_{it}$, $\Psi_i(L) = \begin{pmatrix} \Psi_{uu,i}(L) & \underline{0}^{'} \\ \underline{0} & \Psi_{\nu\nu,i}(L) \end{pmatrix}$. $\underline{w}_{it}$ satisfies the functional central limit theorem $\frac{1}{\sqrt{T}}\sum_{t=1}^{[tr]} \underline{w}_{it} \rightarrow \underline{B}_i = \Psi_i(1)\underline{W}_i$, where $\rightarrow$ denotes convergence in distribution, $\underline{B}_i = (B_{ui}, \underline{B}_{\nu i}^{'})^{'}$, B_{ui} and $\underline{B}_{\nu i}$ are independent, and

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

If we take the time-series average of the equation (48), we have

$$\frac{1}{T}\sum_{t=1}^{T} y_{it} = \alpha_i + \underline{\gamma}^{'}\frac{1}{T}\sum_{t=1}^{T}\underline{x}_{it} + \underline{\delta}_i^{'}\frac{1}{T}\sum_{t=1}^{T}\underline{z}_{it} + \frac{1}{T}\sum_{t=1}^{T} u_{it} \tag{49}$$

By subtracting the previous equation from the equation (46), we obtain:

$$\tilde{y}_{it} = \underline{\gamma}^{'}\tilde{x}_{it} + \underline{\delta}_i^{'}\underline{z}_{it} + \tilde{u}_{it} \tag{50}$$

where $\tilde{y}_{it} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\tilde{\underline{x}}_{it} = \underline{x}_{it} - \frac{1}{T}\sum_{t=1}^{T}\underline{x}_{it}$, $\tilde{y}_{it} = \underline{z}_{it} - \frac{1}{T}\sum_{t=1}^{T}\underline{z}_{it}$, $\tilde{u}_{it} = u_{it} - \frac{1}{T}\sum_{t=1}^{T} u_{it}$.

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

In other words,

$$\begin{aligned} \tilde{\underline{q}}_{1t} &= (\tilde{\underline{x}}_{1t} \;\; \tilde{\underline{z}}_{1t} \;\; \underline{0}^{'} .... \; \underline{0}^{'}) \\ \tilde{\underline{q}}_{2t} &= (\tilde{\underline{x}}_{2t} \;\; \underline{0}^{'} \;\; \tilde{\underline{z}}_{2t} \; .... \; \underline{0}^{'}) \\ &\vdots \\ \tilde{\underline{q}}_{Nt} &= (\tilde{\underline{x}}_{Nt} \; \underline{0}^{'} \; \underline{0}^{'} \; .... \; \tilde{\underline{z}}_{Nt}) \end{aligned} \tag{51}$$

Let the grand coefficient vector be $\underline{\beta} = (\underline{\gamma}^{'}, \delta_1^{'}, ..., \delta_N^{'})^{'}$ and the compact form of the regression $\tilde{y}_{it} = \underline{\beta}^{'} + \tilde{\underline{q}}_{it} + \tilde{u}_{it}$. The panel $DOLS$ estimator for the fixed effect model is β_{NT}, where

$$(\underline{\beta}_{NT} - \beta) = [\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{\underline{q}}_{it}\tilde{\underline{q}}_{it}^{'}]^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{\underline{q}}_{it}\tilde{u}_{it}] \tag{52}$$

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,

$$u_{it}^{\dagger} = \sum_{s=-p_i}^{p_i}\underline{\delta}_{i,s}^{'}\underline{\nu}_{it-s} + u_{it} = \sum_{s=-p_i}^{p_i}\underline{\delta}_{i,s}^{'}\Delta\underline{x}_{it-s} + u_{it} = \underline{\delta}_i^{'}z_{it} + u_{it} \tag{53}$$

into equation (46), we have:

$$\tilde{y}_{it} = \alpha_i + \lambda_i t + \underline{\gamma}^{'} \underline{x}_{it} + \underline{\delta}_i^{'} \tilde{\underline{z}}_{it} + \tilde{u}_{it} \tag{54}$$

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

$$\frac{1}{T}\sum_{t=1}^{T} y_{it} = \alpha_i + \lambda_i(\frac{t+1}{2}) + \underline{\gamma}^{'} \frac{1}{T}\sum_{t=1}^{T} x_{it} + \underline{\delta}_i^{'} \sum_{t=1}^{T} \underline{z}_{it} + \frac{1}{T}\sum_{t=1}^{T} u_{it} \tag{55}$$

where $\frac{1}{T}\sum_{t=1}^{T} t = (\frac{t+1}{2})$. By subtracting the equation (53) from the equation (52), we obtain:

$$\tilde{y}_{it} = \lambda_i \tilde{t} + \underline{\gamma}^{'} \tilde{\underline{x}}_{it} + \underline{\delta}_i^{'} \tilde{\underline{z}}_{it} + \tilde{u}_{it} \tag{56}$$

where we use a 'tilde' to indicates the deviation of an observation from its time-series averages, $\tilde{y}_{it} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\tilde{\underline{x}}_{it} = \underline{x}_{it} - \frac{1}{T}\sum_{t=1}^{T} \underline{x}_{it}$, $\tilde{y}_{it} = \underline{z}_{it} - \frac{1}{T}\sum_{t=1}^{T} \underline{z}_{it}$, $\tilde{u}_{it} = u_{it} - \frac{1}{T}\sum_{t=1}^{T} u_{it}$ and $\tilde{t} = t - \frac{(T+1)}{2}$. To set up the panel DOLS estimator, let $\underline{\lambda}_N = (\lambda_1, \lambda_2, ..., \lambda_N)^{'}$, $\underline{\beta} = (\underline{\lambda}^{'}, \underline{\lambda}_N^{'}, \delta_1^{'}, ..., \delta_1^{'})^{'}$ and,

$$\begin{aligned}
\tilde{\underline{q}}_{1t}^{'} &= (\tilde{\underline{x}}_{1t} \;\; \underline{t} \;\; 0 \; .... \; 0 \;\; \tilde{\underline{z}}_{1t}^{'} \; \underline{0}^{'} .... \; \underline{0}^{'}) \\
\tilde{\underline{q}}_{2t} &= (\tilde{\underline{x}}_{2t} \;\; \underline{0}^{'} \;\; \underline{t} \; .... \; 0 \;\; \underline{0}^{\prime} \; \tilde{\underline{z}}_{2t} \; .... \; \underline{0}^{'}) \\
&\vdots \\
\tilde{\underline{q}}_{Nt} &= (\tilde{\underline{x}}_{Nt} \; \underline{0}^{'} \; \underline{0}^{'} \; .... \;\; \underline{t} \;\; \underline{0}^{'} \; \underline{0}^{'} \; .... \; \tilde{\underline{z}}_{Nt})
\end{aligned} \tag{57}$$

The panel *DOLS* estimator of β is:

$$\beta_{NT} = [\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it} \tilde{\underline{q}}_{it}^{'}]^{-1} [\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\underline{q}}_{it} \tilde{y}_{it}] \tag{58}$$

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 (46), we have:

$$\tilde{y}_{it} = \alpha_i + \lambda_i t + \theta_t + \underline{\gamma}^{'} \underline{x}_{it} + \underline{\delta}_i^{'} \tilde{\underline{z}}_{it} + \tilde{u}_{it} \tag{59}$$

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 $\sum_{j=1}^{N} \underline{\delta}_j^{'} \underline{z}_{jt}$ which complicates estimation of the δ_i coefficients. The estimation problem can be simplified by proceeding sequentially and addressing the endogeneity correction separately from cointegration vector estimation.

To this end, let $y_{it}^{\ddagger}$ be the error from projecting each element of y_{it} onto $\underline{n}_{it} = (1,\text{t}, \underline{z}_{it}^{'})$ and $\underline{x}_{it}^{\ddagger} = \underline{x}_{it} - \Phi_i \underline{n}_{it}$ 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 $\underline{x}_{it}$ into equation (59), we have:

$$\tilde{y}_{it}^{\ddagger} = \underline{\gamma}' \underline{x}_{it}^{\ddagger} + \theta_t + u_{it} \tag{60}$$

To estimate the parameter $\underline{\gamma}$ in the equation (59), equation (60) is used. Taking the cross-sectional average of equation (60), we have:

$$\frac{1}{N}\sum_{j=1}^{N} y_{it}^{\ddagger} = \underline{\gamma}' [\frac{1}{N}\sum_{j=1}^{N} \underline{x}_{it}^{\ddagger}] + \theta_t + \frac{1}{N}\sum_{j=1}^{N} u_{jt} \tag{61}$$

Subtracting equation (61) from equation(60) eliminates the common time effect giving:

$$\tilde{y}_{it}^{\ddagger} = \underline{\gamma}' \underline{x}_{it}^{\ddagger} * + u_{it}^{*}, \tag{62}$$

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

$$\gamma_{NT} = [\sum_{i=1}^{N}\sum_{t=1}^{T} \underline{x}_{it}^{\ddagger *} \underline{x}_{it}^{\ddagger * 0}]^{-1} [\sum_{i=1}^{N}\sum_{t=1}^{T} \underline{x}_{it}^{\ddagger *} y_{it}^{\ddagger *}] \tag{63}$$

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Table 1: **Panel unit root tests. Variables:lnVA**

CH panel tests				
	P_m	Z	L^*	
	3.066	−3.103	−2.979	
	(0.000)	(0.000)	(0.001)	
MP panel tests				
$\hat{r}$	t_a^*	t_b^*	t_a^{*B}	t_b^{*B}
1	−0.990	−1.083	−1.237	−1.048
	(0.161)	(0.139)	(0.128)	(0.147)
BNG panel tests				
$\hat{r}$	$Z_{\hat{e}}^c$	$P_{\hat{e}}^c$	$ADF_{\hat{F}}^c$	
1	−1.589	25.879	−0.787	
	(0.943)	(0.959)	(0.801)	
PS panel tests				
$p*$	$CIPS$	$CIPS^*$		
1	−2.238	−2.238		
	(0.035)	(0.035)		
2	−2.141			
	(0.075)			
3	−1.910			
	(0.280)			
4	−1.641			
	(0.635)			

Notes:
(a) 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. (b) For each variable, the number of common factor estimated ($\hat{r}$) is estimated by the BIC3 criterion, with a maximum number of factor equal to 5. For idiosyncratic components $\hat{e}_{it}$, the pooled unit root statistic test are reported. $P_{\hat{e}}^c$ is a Fisher's type statistic based on a p-valued of the individual ADF tests. Under the null hypothesis, $P_{\hat{e}}^c$ has a distribution whet T tends to infinity and N is fixed. $Z_{\hat{e}}^c$ is the standardized Choi's type test statistic. Under the null hypothesis, $Z_{\hat{e}}^c$ has a $N(0,1)$ distribution. For the idiosyncratic components $\hat{F}_t$, 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 of independent stochastic trends in the common factors a reported. (c) t_a^* and t_b^* tests based on de-factored panel data and computed with a quadratic spectral kernel function. (d) t_a^{*B} and t_b^{*B} are computed with a Barlett kernel function. (e) p-values are in parenthesis.

Table 2: **Panel unit root tests. Variables:lnK**

CH panel tests				
	P_m	Z	L^*	
	1.812 (0.350)	1.588 (0.944)	2.153 (0.984)	
MP panel tests				
$\hat{r}$	t_a^*	t_b^*	t_a^{*B}	t_b^{*B}
1	−11.383 (0.000)	−5.719 (0.000)	−12.765 (0.000)	−6.260 (0.000)
BNG panel tests				
$\hat{r}$	$Z_{\hat{e}}^c$	$P_{\hat{e}}^c$	$ADF_{\hat{F}}^c$	
1	0.859 (0.185)	48.011 (0.180)	−2.534 (0.120)	
PS panel tests				
$p*$	$CIPS$	$CIPS^*$		
1	−1.853 (0.370	−1.853 (0.370)		
2	−1.525 (0.805)			
3	−1.704 (0.550)			
4	−1.349 (0.915)			

Notes:

(a) 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. (b) For each variable, the number of common factor estimated ($\hat{r}$) is estimated by the BIC3 criterion, with a maximum number of factor equal to 5. For idiosyncratic components $\hat{e}_{it}$, the pooled unit root statistic test are reported. $P_{\hat{e}}^c$ is a Fisher's type statistic based on a p-valued of the individual ADF tests. Under the null hypothesis, $P_{\hat{e}}^c$ has a distribution whet T tends to infinity and N is fixed. $Z_{\hat{e}}^c$ is the standardized Choi's type test statistic. Under the null hypothesis, $Z_{\hat{e}}^c$ has a $N(0, 1)$ distribution. For the idiosyncratic components $\hat{F}_t$, 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 of independent stochastic trends in the common factors a reported. (c) t_a^* and t_b^* tests based on de-factored panel data and computed with a quadratic spectral kernel function. (d) t_a^{*B} and t_b^{*B} are computed with a Barlett kernel function. (e) p-values are in parenthesis.

Table 3: **Panel unit root tests. Variables:lnLh**

CH panel tests				
	P_m	Z	L^*	
	2.830	-2.426	-2.407	
	(0.002)	(0.058)	(0.061)	
MP panel tests				
$\hat{r}$	t_a^*	t_b^*	t_a^{*B}	t_b^{*B}
1	-7.036	-3.893	-7.031	-3.858
	(0.000)	(0.000)	(0.000)	(0.000)
BNG panel tests				
$\hat{r}$	$Z_{\hat{e}}^c$	$P_{\hat{e}}^c$	$ADF_{\hat{F}}^c$	
2	0.859	48.011	–	
	(0.185)	(0.180)		
PS panel tests				
$p*$	$CIPS$	$CIPS^*$		
1	-1.853	-1.853		
	(0.370	(0.370)		
2	-1.525			
	(0.805)			
3	-1.704			
	(0.550)			
4	-1.349			
	(0.915)			

Notes:

(a) 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. (b) For each variable, the number of common factor estimated ($\hat{r}$) is estimated by the BIC3 criterion, with a maximum number of factor equal to 5. For idiosyncratic components $\hat{e}_{it}$, the pooled unit root statistic test are reported. $P_{\hat{e}}^c$ is a Fisher's type statistic based on a p-valued of the individual ADF tests. Under the null hypothesis, $P_{\hat{e}}^c$ has a distribution whet T tends to infinity and N is fixed. $Z_{\hat{e}}^c$ is the standardized Choi's type test statistic. Under the null hypothesis, $Z_{\hat{e}}^c$ has a $N(0,1)$ distribution. For the idiosyncratic components $\hat{F}_t$, 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 of independent stochastic trends in the common factors a reported. (c) t_a^* and t_b^* tests based on de-factored panel data and computed with a quadratic spectral kernel function. (d) t_a^{*B} and t_b^{*B} are computed with a Barlett kernel function. (e) p-values are in parenthesis.

Table 4: **Panel cointegration tests results.**

Variables	ADF (Kao)	$Panel{-}t$ $(Pedroni)$	$CUSUM$ $(Westerlund)$	WR_M $(Westerlund)$
$lnVA, lnK, lnLh$	-2.601 (0.004)	2.857 (0.002)	0.911 (0.181)	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. Under the null, the ADF and the Panel-t tests have a standard Normal distribution. (c) In the CUSUM test the null hypothesis is that all individuals of the panel are co-integrated. The Bartlett kernel is $\omega(\frac{j}{M}) = 1 - \frac{j}{(1+M)}$. The optimal Bandwidth for the Bartlett Kernel is $M = [T^{1/3}]$. (d) The WR_M test is developed under the assumption of cross-sectional dependence. 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. (e) numbers in parenthesis are p-values.

Table 5: **Estimation Results. Methods: DOLS and FMOLS (Pedroni's estimators).**

	$DOLS$ (1)	$DOLS$ (2)	$FMOLS$ (3)	$FMOLS$ (4)
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) (1) denotes the $DOLS$ estimator without common time dummies. (b) (2) indicates the $DOLS$ estimator with common time dummies.(c) (3) denotes the $FMOLS$ estimator without common time dummies. (d) (4) indicates the $FMOLS$ with common time dummies. (e) common time are included to control for cross-sectional dependence. (f) numbers in brackets are the t-statistics. (g) $*$ denotes significant at 5% level

Table 6: **Estimation Results. Methods: PDOLS (Mark and Sul estimators).**

	$PDOLS$ (1)	$PDOLS$ (2)	$PDOLS$ (3)	$PDOLS$ (4)
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*) (1) denotes the $PDOLS$ estimator with individual effect and without common time dummies. (*b*) (2) indicates the $PDOLS$ estimator with individual effect and common time dummies.(*c*) (3) denotes the $PDOLS$ estimator with individual effect and heterogenous trends and without common time dummies. (*d*) (4) indicates the $PDOLS$ estimator with individual effect, heterogenous trends and common time dummies. (*e*) common time dummies allows to control for cross-sectional dependence. (*d*) numbers in brackets are the t-statistics based on corrected parametric standard errors. (*f*) numbers in brackets are the t-statistics. (*g*) $*$ denotes significant at 5% level.