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Human capital, technological spillovers and development across OECD countries

by

Rosa Bernardini Papalia[♣], Silvia Bertarelli[♦], Carlo Filippucci[♠]

Abstract
In this paper, we study the relationship between the level of development of an economy and returns to different levels of education for the panel of OECD countries over the 1965-2004 period, in a club convergence framework. The connection between growth and human capital measures of primary, secondary and tertiary education in a multiple-club spatial convergence model with non linearities and spatial dependence is considered. By decomposing total schooling into its three constituent parts, we are able to evaluate their impact on regional growth without imposing homogeneous returns from each level of education. We contribute to the identification of two regimes for OECD countries, each characterized by different returns on physical and human capital accumulation and technological spillovers. We also find that the non-monotonic pattern of convergence is strongly influenced by human capital stocks and technology diffusion process is stronger in the club less close to the technological frontier.

1. Introduction

In this paper, we assess the existence of club convergence across OECD countries over the period 1965-2004 with the objective of evaluating the growth-education nexus and by focusing the attention on the composition of human capital as well as on its level, and on non linear convergence processes. Club convergence means that economies converge if their initial conditions guarantee the attraction to the same steady state equilibrium conditioned by their structural characteristics. This behavior is related to the presence of multiple steady state equilibria.
Growth theories establish that human capital positively affects income levels and growth rates, while empirical evidence on this issue is mixed (Acemoglu, 2009; Temple, 1999). Mankiw et al. (1992) show that the accumulation of human capital, measured in terms of secondary school enrollment, contribute positively to per capita GDP growth rates. Recent research on human capital has focused on stock measures of human capital. In this case, the effects of education and growth are positive and statistically significant only for the countries with the lowest level of education (Krueger and Lindahl, 2001).
Two plausible reasons for this puzzle which represent the basic motivations of our contribution and are related to education that promotes both innovation activities and imitation of existing technologies. Human capital is crucial in innovation activities, especially in technologically advanced countries. Human capital also favors the adoption of new technologies developed

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elsewhere. However, imitation and innovation require different types of human capital. It is reasonable to assume that unskilled human capital is better suited to imitation than skilled workers, while the reverse is true for innovation (Vandenbussche et al., 2006). Moreover, human capital is important in economic growth given that a convergence process will be effective only if the stock of human capital is greater than a threshold value, and positive effects of financial development emerge when a country has sufficient high levels of education, in line with Rioja and Valev (2004).

Empirical evidence on convergence suggests that regions and countries are not homogenous and not independent units. It is necessary to incorporate heterogeneity by making a further distinction between the concepts of absolute location (spatial heterogeneity) and relative location (spatial dependence). Absolute location refers to the impact of being located at a particular point in space. Relative location considers relevant the position of a country relative to other countries.

From a theoretical perspective heterogeneity is strictly connected with non linearities, while spatial dependence may capture human capital spillovers. Non linearities may be caused by heterogeneous country characteristics, imperfections and other variables causing non-convexities in the production function. They could be the result of different initial conditions that induce the choice of different technologies (Ciccone and Matsuyama, 1996; Galor and Zeira, 1993) or technology is CES (Masanjala and Papageorgiou, 2004). Non linear growth processes imply multiple steady states. Multiple equilibria may be generated by the presence of threshold externalities of accumulated factors (Azariadis and Drazen, 1990) and cross country differences in the level of financial development (Acemoglu and Zilibotti, 1997). Models of endogenous growth often emphasize the importance of technological, physical and human capital spillovers. Such spillovers are connected to i) human capital and institutional differentials ii) bilateral channels such as trade and foreign direct investment (Coe *et al*., 1995; Keller, 1998). The magnitude of these spillovers depends on the patterns of spatial dependence among countries.

The connection between growth and human capital measures of primary, secondary and tertiary education in a multiple-club spatial convergence model with non linearity and spatial dependence has been considered in this paper and an application is suggested for OECD countries over the 1965-2004 period. By decomposing total schooling into its three constituent parts, we are able to evaluate their impact on growth without imposing homogeneous returns from each level of education. This paper applies and generalizes a technique developed in Bernardini Papalia and Bertarelli (2010), by explicitly modeling non linearities and spatial dependence simultaneity within a panel data framework.

Specifically, the number of groups and the countries within each group are identified and a multiple regime system of convergence equations is estimated. Our proposal is to develop a two stage strategy to identify and estimate a multiple club convergence model, which introduces a GME estimation procedure in presence of spatial heterogeneity, spatial dependence and non linearities exploiting information on clustering schemes identified by a mapping analysis. This technique is suggested to correct for biases: (i) connected to model specification problems (omitted variable bias), (ii) arising from simultaneity, miss-specified dynamics and/or measurement errors (Golan *et al*., 1996). At the first stage, unobserved total factor productivity (TFP) differentials across countries are identified by specifying a mapping structure in a convergence model with non linearities and spatial dependence. At the second step of the analysis, a multiple-club spatial convergence model, where clubs correspond to subsets of total observations, as identified at the first stage of the analysis is estimated.

The paper is organized as follows. Section 2 outlines the role of human capital in the growth process and introduces multiple club spatial convergence models with non linearities, spatial heterogeneity and spatial dependence. Section 3 presents the approach used to identify convergence clusters by a mapping structure. A generalized maximum entropy estimation procedure is also developed and discussed in section 3.2. Section 4 introduces alternative spatial two-club convergence model specifications. Data description and findings for the OECD sample are reported in section 5. Last section lists some potential advantages and investigations of the proposed approach.

2. The role of human capital in club convergence

Mankiw et al. (1992) show that the accumulation of human capital, measured in terms of secondary school enrollment, contribute positively to per capita GDP growth rates. Recent research on human capital has questioned this result by focusing on stock measures of human capital and the resulting evidence is mixed. Two plausible reasons for this puzzle are related to the fact that education favors both innovation activities and the imitation of existing technologies.

With reference to innovation, the stock of human capital plays a crucial role, given that the level of technological development in a country is conditioned by factor endowment including skilled workers, as emerges from the literature on appropriate technology (Acemoglu and Zilibotti, 2001).

With reference to the latter reason, traditional models of endogenous growth often emphasize the importance of technological, physical and human capital spillovers. However, knowledge is assumed to be perfectly shared by all countries in the economy and this is in contrast with empirical evidence on costly and time consuming imitation processes (see Acemoglu, 2009). Alternatively, the wide literature on technology diffusion assumes differences in country's capacity to adopt new technological knowledge, connecting them to human capital and institutional differentials (Benhabib and Spiegel, 2005). From an empirical point of view, the effect of education on growth is positive and statistically significant only for the countries with the lowest level of education (Krueger and Lindahl, 2001). This result is justified with a technological catching up process, which is effective only if the stock of human capital is greater than a threshold value as in Benhabib and Spiegel (2005). Non linear effects may be introduced to deal for this idea.

Another view on technology diffusion across countries emphasizes the empirical importance of bilateral channels such as trade, especially of specialized and advanced intermediate products, and foreign direct investment. International externalities emerge in terms of monetary and technological spillovers and display heterogeneous patterns along the geographical dimension. When they are connected to geographical distance between country pairs, such spillovers may be captured by spatial dependence effects. If spatial externalities are introduced in theoretical growth models convergence equations with spatial autocorrelation can be obtained. Growth models with spillovers arising from geographical proximity have been derived by Ertur and Koch (2007), also providing an empirical evaluation of spatial dependence in convergence processes. Durlauf and Quah (1999) discuss the possibility of spatial interdependence in terms of human capital spillovers and argue that their presence markedly influence the dynamics of convergence. In the presence of technological externalities (Benhabib and Spiegel, 1994) or pecuniary externalities (Acemoglu, 1996; Redding, 1996) social returns are greater than private returns on education. Individual-based analyses measure only private returns to education, while macro studies consider returns at aggregate level. In this view, the connection from a macroeconomic perspective between growth and human capital measures could enrich microeconomic analyses especially for economic policy purposes.

Finally, performing imitation and innovation require different types of human capital. It is reasonable to assume that unskilled human capital is better suited to imitation, while the reverse is true for innovation (Vandenbussche et al., 2006). On this basis it seems necessary to focus on a country's distance to the technological frontier and on the composition of the stock of human capital in a simultaneous way.

3. Identification of convergence clubs

Several approaches have been performed to evaluate the composition of convergence clubs in models of economic growth. In theoretical club convergence models, imperfections and other variables such as human capital, income distribution, capital market imperfections, externalities, and imperfectly competitive market structures, causing non-convexities in the production function are considered to deal with non linearities (Azariadis and Stachurski, 2005). In a theoretical perspective non linearities can be connected with the internal sources of factor accumulation (Peretto, 1999), could be the result of different adoption speeds of technological spillovers (Parente and Prescott 1994). However, economic theory does not provide guidance to define the number of groups of regional economies that interact more with each other than with those outside, and to explain the way in which the explanatory variables defining the initial conditions determines clubs.

Exogenous and endogenous techniques have been proposed with the aim of determining different regimes. The former class of exogenous procedures comprises: (i) a priori criteria, like the belonging to a geographic zone or some per capita GDP cut-offs or exogenous core-periphery division; and (ii) exploratory spatial data analyses (ESDA), based on some indicators of global and local spatial autocorrelation of the explanatory variables as per capita GDP, human and physical capital. Endogenous techniques include all the statistical techniques that endogenously determine clubs of regions on the basis of a number of conditioning variables which reflect initial conditions, structural characteristics, economic activity and other effects associated with physical and human capital stocks. As far as multiple control variables are used it is possible to identify the dominating variable as an element useful in identifying multiple regimes. Within the endogenous approaches, several techniques have been developed, as the regression tree method (Durlauf and Johnson, 1995), or techniques based on multivariate test for stationary (Corrado *et al*., 2005). Alfò *et al*. (2008) identify clubs through the analysis of latent structures. Canova (2004) applies a Bayesian technique to find two clubs of OECD countries. Maasoumi *et al*. (2007) use robust nonparametric methods capable of providing consistent estimates of the unknown probability density functions of growth rates and propose new concepts and measures of convergence that are based on entropies distances and dominance relations between groups of countries over time.

Our approach provides a suitable identification of clubs by estimating unobserved components within the conditional convergence framework that may represent a good approximation of TFP levels, as proposed by Islam (1995) and Caselli et al. (1996). By introducing a mapping model, the idea is to single out the role and the weight of unobserved variables connected to the presence of agglomeration externalities, to the quality of institutions, and other variables, which are relevant in shaping a country's technological and structural characteristics.

The analysis for OECD countries gives the possibility to contribute to the debate on the identification of clubs across a small sample of countries whose results are still ambiguous. In fact previous studies on convergence for OECD countries indicate some potential puzzles. Early studies (for example Mankiw et al., 1992) found evidence of absolute convergence for OECD countries. Within the time series approach, Bernard and Durlauf (1995) rejected the convergence hypothesis of OECD countries using standard univariate and multivariate time series techniques and found more than one common long run factor. Canova (2004) applied a Bayesian technique to find two clubs for OECD countries using initial income as a mean to order and group countries.

3.1 Clubs identification: The mapping model

In a convergence analysis framework, a mapping model defines the spatial position of a region's TFP level in terms of different unobserved dimensions weighted by the variables' features. The variability in both cross-region specific unobserved characteristics and time invariant components is considered. The resulting position of the unobserved variables on the M-dimensional map and the country's importance weights for these dimensions are derived.

Specifically, the individual-effect term in the conditional growth model specification is estimated and used to define the spatial position of a country's TFP level on the M-dimensional map, in terms of different unobserved dimensions weighted by the variables' features.

In this framework, the interpretation of the dimensions of a map is aimed at endogenously identifying the determinants of TFP differences. In addition, this type of information on initial conditions is recovered in an endogenous way, without any *ex ante* (and somewhat subjective) selection and facilitates the interpretation of the cluster outcomes, providing a measure of different unobserved dimensions.

According to most recent economic contributions on growth convergence we start by specifying a dynamic panel model with country fixed effects as follows:

$$\ln y_{it} = \beta \ln y_{it-1} + \gamma' D_{it-1} + \mu_i + \upsilon_t + u_{it} \qquad (1)$$

Individual effects μ_i capture differences on the initial TFP level and other time-invariant omitted variables, ln y_{it-1} refers to the endogenous lagged per capita GDP level, υ_t refers to time fixed effects. In the club convergence literature individual fixed effects correspond to initial conditions for technological characteristics and institutions and strongly influence the formation of clubs[1]. Following Mankiw *et al*. (1992), the vector D_{it-1} gives the determinants of the steady state output and consists of a set of country-specific explanatory variables suggested by the theory.

In formal terms, the location map can be obtained by using a two-stage process. First, the parameters of the growth model (eq. 1) are estimated and the covariance matrix of unobserved components μ_i's is computed. Then this matrix is used as an input in multidimensional scaling (MDS) to obtain their locations in a multi-attribute space. In general MDS attempts to arrange "objects" in a space with a particular number of dimensions in order to reproduce the observed distances. MDS actually moves objects around in the space defined by the requested number of dimensions, and checks how well the distances between objects can be reproduced by the new configuration. A function minimization algorithm evaluates different configurations aiming at maximizing the goodness-of-fit. The smaller the value of the loss function, called stress value, the better is the fit of the reproduced distance matrix to the observed distance matrix.

In our procedure the dissimilarity matrix is used to represent TFP data into a two-dimensional Euclidean space, by recovering their coordinates[2]. The map will plot each point, whose proximity indicates how similar they are. The dimensions must be labeled and therefore interpreted by the researcher. We assume that the time-invariant effect for region i, μ_i, is a linear function of the country's time invariant attributes which lie for simplicity within a two-dimension map, such as:

$$\mu_i = s_1 l_{1i} + s_2 l_{2i} + \xi_i \qquad (2)$$

where the parameters s_1 and s_2 are modeled as a function of region's characteristics, the coordinates (l_{1i}, l_{2i}) represent the location (to be estimated) of the unobserved effect on the map, and ξ_i is a random error with zero mean.

Given that this procedure endogenously identifies the determinants of TFP differences and in order to minimize our subjective judgment, we prefer to follow growth theory in the interpretation of the map dimensions (l_{1i}, l_{2i}). In this case, the approach may capture the contribution of national unobserved variables such as the quality of institutions, and the determinants of technological and structural characteristics[3]. It should be noted again that this approach has the advantage over the more traditional approaches to simultaneously identify the main factors that provide an indirect measure of unknown invariant TFP (dis)similarities across countries, and can also control for any residual spatial dependence.

3.2 Generalized Maximum Entropy Estimation of fixed effects in dynamic spatial panel models:

Panel models give us the advantage of introducing and estimating fixed effects in the conditional convergence model to identify convergence clubs and to allow for *spatial unobserved*

[1] Unobservable TFP levels were obtained through a conditional convergence equation of per capita GDP by Islam (1995) and Caselli *et al*. (1996), assuming that TFP is a stationary process.

[2] Cluster analysis is similar to multi dimensional scaling in that both examine inter-object similarity by examining the complete set of interdependent relationships. The difference is that multi dimensional scaling identifies underlying dimensions, while cluster analysis identifies only clusters.

[3] By 'institutions' we mean various aspects of law enforcement, the functioning of markets, quality of human capital, inequality and social conflicts, democracy, political stability, government corruption, the health system, financial institutions, etc.

heterogeneity among spatial units. Nevertheless, since we are observing N different countries over time, we have to take into account potential *spatial dependence* due to the spatial interaction between the economic agents belonging to contiguous countries (Bernardini Papalia 2008a,b). Spatial dependence effects capture monetary and technological spillovers since they are connected to geographical distance between country pairs.

For the *spatial dependence*, two main forms may be distinguished (Anselin, 1988). The first form introduces a spatial error autocorrelation into the model specification which describes how GDP per capita in a country can be affected by a shock in GDP per capita in other countries: shocks are correlated spatially. In the second form, spatial dependence is captured by a spatial lag of the dependent variable. In the latter formulation, we can see if and how GDP per capita in a country is affected by those of neighboring countries.

In all cases, in the estimation of the resulting conditional convergence model it is essential to deal with endogeneity of the spatial lag term as well as of potential endogeneity of the lagged GDP per capita and other explanatory variables. In estimating dynamic panel data models, all the traditional estimation procedures (aggregate time series regressions of group averages; cross-section regressions of averages over time; pooled regressions with fixed or random intercepts; separate regressions for each group, where coefficient estimates are averaged over these groups) yield inconsistent estimators when T is small even if N is large. In addition, when the number of observations is smaller than the number of parameters, the values of unknown parameters cannot be uniquely identified with classical estimation techniques, such as ordinary least squares (OLS).

Our goal is to introduce a GME approach which produces consistent parameter estimates of a conditional convergence model in presence of collinearity and endogeneity of lagged dependent variable, spatial lag variables, and some explanatory variables such as fiscal policy and openness degree.

This technique is here suggested with the aim of correcting for biases: (i) connected to model specification problems (omitted variable bias), (ii) arising from simultaneity, miss-specified dynamics and/or measurement errors. The GME-based estimator is consistent and asymptotically normal, and can achieve efficiency gains over traditional estimators from the prior information that is incorporated into the approach[4].

The specification of the traditional dynamic fixed effects panel model including spatial error autocorrelation (SAR model) is:

$$\begin{aligned} &\ln y_{it} = \beta \ln y_{it-1} + \gamma' D_{it-1} + \mu_i + \upsilon_t + u_{it} \\ &u_{it} = \delta W u_{it} + \varepsilon_{it} \\ &E(\varepsilon_{it}) = 0 \quad E(\varepsilon_{it}\varepsilon_{it}') = \sigma^2 I_N \end{aligned} \tag{3}$$

while the specification model extended with a spatially lagged dependent variable (spatial LAG model) is given by:

$$\begin{aligned} &\ln y_{it} = \rho W \ln y_{it} + \beta \ln y_{it-1} + \gamma' D_{it-1} + \mu_i + \upsilon_t + \varepsilon_{it} \\ &E(\varepsilon_{it}) = 0 \quad E(\varepsilon_{it}\varepsilon_{it}') = \sigma^2 I_N \end{aligned} \tag{4}$$

The SAR model is associated to global spatial externalities, where all locations are related to each other. Therefore, a shock affecting one location diffuses to all other locations in the sample. The spatial effects captured by the spatial LAG model are global in the sense that the model links all the regions in the system. In this case, the dependent variable in a location is related to all the dependent variables in other locations.

In the spatial error specification, δ is usually called the spatial autocorrelation coefficient, while ρ in the spatial lag specification is referred to as the spatial autoregressive coefficient. The spatial

[4] For background on GME estimation approach, also developed in a panel data framework, and finalized to performance comparisons to other estimation methodologies, see Golan *et al*. (1996, 2008).

weights matrix W_N of non-stochastic time constant weights is a ($N\times N$) matrix in which the rows and columns correspond to the cross-sectional observations. An element w_{ij} of the matrix expresses the prior strength of the interaction between location i (in the row of the matrix) and location j (columns). This can be interpreted as the presence and strength of a link between nodes (observations) in a network representation that matches the spatial weights structure. In most application, the choice is driven by geographic criteria, such as contiguity (sharing a common border) or distance, including nearest neighbor distance (Anselin 1988).

In this work, GME is introduced by generalizing the approach suggested in Bernardini Papalia (2008a, b) to deal with the Dynamic models for Spatial Panel models exhibiting both dependence in the dependent variable and the error structure. This model can be expressed concisely, in stacked form, as:

$$
\begin{aligned}
y &= \rho\left(I_T \otimes W_N\right)y + X\beta + u \\
u &= \lambda W_N u + \varepsilon \\
E\left(\varepsilon\varepsilon'\right) &= \sigma_\varepsilon^2 I_{NT}
\end{aligned}
\tag{5}
$$

with y as a $NT\times 1$ vector, X as a $NT\times K$ matrix and ε as a $NT\times 1$ vector, ρ is the scalar spatial autoregressive parameter, and the other notation is as before. The set of k explanatory variables X is extended to include the spatial lagged dependent variables $\ln y_{it-1}$ and country and time fixed effects ($X = \left[\ln y_{iy-1} \vdots \left(\iota_T \otimes I_N\right) \vdots \left(I_T \otimes \iota_N\right)\right]$); $\otimes$ is the Kronecker product operator, ι_T and ι_N are $T\times 1$ and $N\times 1$ vectors of all unity elements respectively, and I_N and I_T are identity matrices of dimension N and T, respectively.

Our proposal is to introduce a GME formulation with the objective of recovering the unknown parameters of the fixed effects spatial panel model as specified in the equation (5) and dealing with the problems due to the endogeneity of the spatial lag and fixed effects components (Golan 1996). Following the Information-theoretic GME idea, based on the Shannon entropy principle, we first proceed by reformulating all parameters and noise components of the model (5) as set of proper probabilities. p indicates a probability distribution for parameters and r a probability distribution for errors, defined on some support spaces (Z support space for parameters and V support space for random errors).

The GME approach considers the *Re-Parameterization* of the unknown parameters and the disturbance terms, as a convex combination *of expected value of a discrete random variable*. The coefficients are all Re-Parameterized as expected values of discrete random variable with M fixed points for the coefficients and J for the errors. The Re-Parameterized coefficients are defined as follows ρ=$\left(Z^\rho p^\rho\right)$; β=$\left(Z^\beta p^\beta\right)$; u=$\left(V^u r^u\right)$; ε=$\left(V^\varepsilon r^\varepsilon\right)$. β is enlarged to include time and fixed effects. The matrices (Z^β, Z^ρ) and (V^u, V^ε) define the support fixed points for the re-parameterization of the coefficients and the error terms. The matrices Z and V are diagonal and the generic matrix element is represented respectively by the vectors $\mathbf{z}_k^{'} = [-c \quad -c/2 \quad 0 \quad c/2 \quad c]$ and $\mathbf{v}_h^{'} = [-b \quad -b/2 \quad 0 \quad b/2 \quad b]$.

These vectors define the support values, called *Fixed Points* (FPs), usually with five elements (M=N=5), uniformly and symmetrically chosen around zero with equally spaced distance discrete points.

However, the choice of **v** for the disturbance term clearly depends on the sample observed as well as any conceptual or empirical information about the underlying error. If a conceptual or empirical information does not exist, then **v** may be specified to be uniformly and symmetrically distributed around zero (Golan et al., 1996). Chebychev's inequality may be used as a conservative means of specifying sets of error bounds. For any random variable **V**, with E(**V**)= 0 and Var(**V**) =σ^2, the inequality provides $P\{|\mathbf{V}|<d\cdot\sigma\} \geq 1-d^{-2}$ with d >0.

Given some excluded tail probability, Chebychev's error bounds are $\mathbf{v}_1$=-d·σ and $\mathbf{v}_n$= d·σ, as for example: $[-d\cdot\sigma \quad -d\cdot\sigma/2 \quad 0 \quad d\cdot\sigma/2 \quad d\cdot\sigma]$; or these bounds can be obtained by the 3σ rule which of Pukelshiem (1994).
Following the approach proposed in Bernardini Papalia (2008a, b), the model (5) can be *Re-Formulated* in terms of the re-parameterized coefficients as follows.
The coefficients and the error terms are estimated by recovering the probability distribution of the discrete random variables set. The vectors $p=vec(p^{\beta}, p^{\rho})$ and $r=vec(r^{u}, r^{\varepsilon})$ are vectors of proper probability distributions for parameters and errors, respectively, while p^{β}, p^{ρ}, r^{ε}, r^{u}, are calculated by the maximization of the following entropy function:

$$\max_{p_i, r_i} H(p,r) = -p'\ln p - r'\ln r \tag{6}$$

subjected to the *consistency* and *adding-up constraints*. The consistency constraint represents the information about the data expressed by the reformulated model in the equation (5):

$$Y = (Z^{\rho} p^{\rho})(I_T \otimes W_N)Y + X(Z^{\beta} p^{\beta}) + (Z^{\lambda} p^{\lambda})W_N (V^{u} r^{u}) + (V^{\varepsilon} r^{\varepsilon}); \tag{7}$$

The *adding-up constraints* impose that the sum of each coefficients and the error terms probability vector have to be equal to 1.
For the empirical analysis on club convergence two points of interest should be noted here. First, the system estimation approach facilitates testing of hypotheses involving cross equation restrictions such as testing the equality of total factor productivities in two neighboring countries. Second, by using the GME procedure it is possible to derive an estimator even if the number of countries involved, N, is more than the number of time periods, T, and the corresponding variance-covariance matrix for errors is singular.

4. Specification of the multiple regime model

The second step of our approach is focused on a spatial multiple regime specification and gives direct support to the conjecture implied by the mapping representation developed in the previous step procedure. Again, spillovers connected to geographical distance are modeled in terms of spatial dependence effects.
Let consider for sake of simplicity two clubs only, j = 1, 2. Clubs correspond to subsets of countries identified by means of the mapping analysis. Each club may be represented by a conditional convergence equation. The *two-club growth model* in the LAG form can formally be represented as the set of two equations, j = 1, 2:

$$y_j = \rho_j (I_T \otimes W_N) y_j + X_j \beta_j + \varepsilon_j, \qquad j = 1,2 \tag{8}$$

where y_j is $N_jT\times 1$, X is $N_jT\times K_j$, β_j is $k_j\times 1$, and ε is a $N_jT\times 1$ error vector, ρ_j is the scalar spatial autoregressive parameter, and the other notation is as before. The set of k explanatory variables X_j is again extended to include the spatial lagged dependent variables $\ln y_{it-1}$ and country and time fixed effects ($X = [\ln y_{iy-1} \vdots (\iota_T \otimes I_N) \vdots (I_T \otimes \iota_N)]$); $\otimes$ is the Kronecker product operator, ι_T and ι_N are $T\times 1$ and $N\times 1$ vectors of all unity elements respectively, and I_N and I_T are identity matrices of dimension N and T, respectively.
The model with a constant error variance over the whole set of observations given by:

$$E(\varepsilon\varepsilon') = \sigma_{\varepsilon}^2 I_{NT} \tag{9}$$

refers to the *classical two-club convergence model*. As an alternative, the *two-club convergence model with group wise heteroskedasticity* assumes a different error variance in each of the two clubs of countries.
There is club convergence when parameter estimates for the lagged dependent variable of each club are significantly negative and different from each other.
The *two-club growth model* in the SEM model assumes that the error ε_j follows a spatial autoregressive process and can be formalized as follows:

$$y_j = \rho_j\left(I_T \otimes W_N\right)y_j + X_j\beta_j + \varepsilon_j, \qquad j = 1,2$$
$$\varepsilon_j = \left(I_T \otimes \lambda_j W_N\right)\varepsilon_j + u_j \tag{10}$$

where y_j is $N_jT\times1$, X is $N_jT\times K_j$, β_j is $k_j\times1$, and ε_j is a $N_jT\times1$ error vector, λ_j is the scalar spatial autoregressive parameter, and other notation is as before. The set of k explanatory variables X_j is again enlarged to include the spatial lagged dependent variables $\ln y_{it-1}$ and country and time fixed effects ($X = \left[\ln y_{iy-1} \vdots (\iota_T \otimes I_N) \vdots (I_T \otimes \iota_N)\right]$); $\otimes$ is the Kronecker product operator, ι_T and ι_N are $T\times1$ and $N\times1$ vectors of all unity elements respectively, and I_N and I_T are identity matrices of dimension N and T, respectively.

As pointed up in the previous section, consistent and asymptotically normal estimates may be obtained by using the generalized maximum entropy (GME) estimation approach. GME formulations of Spatial LAG and Spatial SEM dynamic panel data models are introduced and discussed in Bernardini Papalia (2008a, b).

5. The case of OECD

In this section, we show that OECD countries are characterized by different returns on physical and human capital accumulation and technological spillovers. We admit the presence of spatial heterogeneity in slope coefficients, spatial dependence and non monotonic convergence. In this view, we will apply the methodology presented in the previous sections.

The analysis across OECD countries covers the 1965-2004 periods and is based on Penn World Table (PWT) 6.2 data set on GDP and investment at 2000 constant prices, government share of GDP. Data on active population (15-64) are from ILO-Laborsta (1980-2007) and United Nations, World Population Prospects (1965-2007). Real per capita GDP is calculated as a ratio of real GDP and active population, the saving rate in physical capital is given by the ratio of investment and GDP in real terms. Moreover, we add to the active population growth rate, a constant value of 0.05 to take account of the exogenous technological growth rate and the depreciation rate. This value has been chosen to match data, as in Mankiw *et al*. (1992) among many others, and changes in this assumption have little effect on the estimates.

We also consider school attainment levels in order to examine the contribution of human capital in the technology adoption process, as emphasized by Benhabib and Spiegel (2005). The education stock series from World Bank for the years 1960-90 are used. The average education stock measures the mean school years of education of the working age population (defined as the population between the ages 15 and 64), and is the sum of primary, secondary and post-secondary average education stock. We also consider decomposed human capital measures in terms of primary, secondary and tertiary education, according to Vandebussche *et al*. (2006). Human capital data updating to 2004 is obtained by extrapolation.

In line with the empirical literature on convergence, other control variables have been included: the government consumption ratio over GDP, the degree of openness measured by the sum of exports and imports over GDP, CPI inflation as a measure of macroeconomic instability and financial development.[5] The ratio of trade flows (export plus import) to GDP is used as a measure of openness, from PWT 6.2. CPI inflation is used as a measure of macroeconomic instability. Financial development (data source: World Bank) is represented by commercial bank deposit money divided by (deposit money plus central) bank assets to measure the relative importance of commercial banks versus central banks in allocating savings.

Moreover, the idea of a technological catching up process which is effective only if the stock of human capital is greater than a threshold value (Benhabib and Spiegel, 2005) asks for introducing non linear effects. In addition, financial development can have positive effects provided that a

[5] Alternative specifications, with and without some additional explanatory variables, have been the objective of a preliminary analysis. The entropy ratio Chi-squared statistic (Golan *et al*., 1996) has been used to analyze the relative explanatory power and reduction of uncertainty of each group of variables used.

country has sufficient high levels of tertiary education as argued by Rioja and Valev (2004). Tertiary school attainment level is suggested as a threshold variable for financial development and primary, secondary and tertiary school attainment levels as thresholds for the lagged per capita GDP level. Time effects control for the presence of a time trend component and of a stochastic trend common across countries (the common evolution of technology frontier).

All final data are expressed in logs. As it is common with most recent contributions, we employ panel data over 5-year periods to eliminate the business cycle component. For each country, data are available for seven 5-year time intervals: 1970-1974, 1975-1979, 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004[6]. Another additional 5-year period (1965-1969) has been used to construct time lagged variables.

5.1 Step I procedure: identification of clubs

The relationship describing the evolution of regional per-capita GDP is specified through a dynamic model with fixed effects, spatial error and spatial lag dependence (see equation 5). The growth regression model is estimated assuming a threshold non-linear specification in terms of per capita GDP levels. In order to overcome problems connected to regressors collinearity and endogeneity, a generalized maximum entropy approach is used. The choice is grounded on a set of diagnostic tests, which have been performed with reference to a pooled OLS estimator for a model specification without spatial variables (table 1)[7]. OLS estimates display spatial heterogeneity, heteroskedasticity, non normality and collinearity problems. Standard tests confirm endogeneity for lagged per capita GDP level as well as for fiscal policy and openness. Spatial dependence is confirmed by spatial correlation tests on GME residuals for a non spatial model specification[8]. In our analysis, the weight matrix to model spatial dependence is computed by means of the distance between the capital cities, where the critical cut-off value is given by the first quartile (such results are robust to some other definitions of the limit value, e.g. median). GME estimates are summarized in table 2.

With reference to mapping analysis, described in section 3.1, the presence of two groups is confirmed (see table 3 for country groupings). While the number of clubs is in accordance with Canova (2004), country groupings are different. Club 1 includes 15 countries, while Australia, Italy, Korea, Mexico, Portugal, Spain, Switzerland and Turkey join the club 2.

Several determinants of TFP dimensions have been identified from simple scatter plots of some World Bank governance indicators (Kaufmann et al., 2009), quality of education and average private returns of education (Cohen and Soto, 2007) for each dimension. Good institutions and high quality of human capital are positively correlated with one dimension. Our finding confirms the evidence of Alfò *et al*. (2008) who argue that the latent variable defining regimes may be related to institutions, which is finding is in line with Hall and Jones (1999) and Acemoglu et al. (2005) which pose great importance on quality or appropriateness of institutions. In addition human capital has an important role in the technology catch up among countries (Benhabib and Spiegel, 2005).

5.2 Step II – differences in growth determinants across clubs

After having identified two sub-groups of OECD countries, the analysis of differences in growth determinants across clubs is to be performed, by estimating a system of two convergence equations is estimated. The model specifications are given by (8) and (10) where all explanatory variables are exactly the same used in the previous step. The empirical estimation of the club convergence system, by means of spatial SEM, spatial LAG and mixed models, poses all endogeneity and ill-posed problems outlined in step I procedure. Again, a GME approach is used. All spatial models assume that growth determinants and spatial effects are not identical across regimes. The Wald test on the homogeneity of the parameters across equations points out to the superiority of a

[6] Other studies have taken averages over 5-*year* periods, like Islam (1995) and Caselli *et al*. (1996) among others.

[7] Detailed results are available upon request.

[8] Moran's I and Geary's C tests cannot accept the null hypothesis of global spatial independence (0.123; p-value: 0.024 for the former; 0.878; p-value: 0.096 for the latter).

specification with heterogeneous slope coefficients. Since the LM Lag test value exceeds the LM Error test value, the two tests point to the presence of spatial lag dependence rather than spatial error autocorrelation. Our results indicate strong evidence of positive spatial dependence in terms of a spatial lag model. Therefore, per capita GDP in a country is affected by those of neighboring countries within each club. In addition, complementarity's effects from GDP levels in neighboring regions arise and their magnitude is different across regimes. These international spillovers are stronger in followers countries than in leader ones. Findings concerning the spatial lag model are presented in table 4, while those for the other spatial specifications are available upon request[9].

From club convergence analysis a link between stages of development and returns to levels of education emerges, in line with Vandebussche *et al*. (2006). The positive effect of primary school attainment in laggard countries is stronger (about five times) than leading economies effect. Secondary school attainment gives positive effects in both clubs; however return on secondary schooling is higher in countries close to the technological frontier than other countries. While primary and secondary schooling coefficients are positive, tertiary school attainment shows negative effects in followers countries, while leader club coefficient is not significant. The composition of human capital is relevant for growth.

The negative effect of tertiary education is not new in the literature studying the effects of human capital composition on growth. Theoretical explanations point to several reasons[10]. High education performs a signaling function in the job market, or stimulates rent-seeking activities rather than productive ones. Vandebussche *et al*. (2006) argue that highly educated labor force may have positive effects with the proximity to the technological frontier because only countries at the frontier are likely to innovate rather than to simply imitate. Our findings confirm this idea. When countries are less close from the frontier, their investment in high education is not coupled with (sufficient) innovation activities and therefore high skilled worker are used in other non innovation activities where signaling and rent-seeking strategies are more likely.

We also find that the non-monotonic pattern of convergence within each club is strongly influenced by human capital stocks. In the leading group, significant non linear effects of primary and secondary educational attainment emerge. In the other club, primary and tertiary attainment levels show significant coefficients with opposite signs, positive and negative respectively.

The interaction between financial development and human capital makes a significant and positive contribution to growth only in the follower countries club. This result is coherent with previous evidence (Ketteni et al., 2005; Stengos and Liang, 2005; Rioja and Valev, 2004).

With reference to other regressors, the effect of population growth rate (*lndx*) is negative and significant for both clubs. The investment in physical capital (*lsk*) has positive and significant effects on growth, with the highest coefficient in club 2. In this group of countries significant returns could also come from the accumulation of new capital goods. The degree of openness has a positive effect for all clubs, with a stronger effect for club 2. Fiscal expenditure and inflation have positive effects for all clubs. With reference to all explanatory variables, the computation of the Wald test on the homogeneity of the parameters across equations point out to the superiority of a model specification with heterogeneous slope coefficients.

6. Remarks and conclusions

In this paper a two-step procedure has been applied to identify multiple regimes across OECD countries and to estimate a multiple spatial convergence club model that also incorporates non linearities and spatial dependence. The entropy-based estimation procedure overcomes problems of

[9] Some differences emerge by comparing estimates of error and lag models. In both specifications, we obtain different coefficients of the lagged per capita income for regime A and B, which yield different convergence rates across regimes. Since the LM Lag test value exceeds the LM Error test value, the two tests point to the presence of spatial lag dependence rather than spatial error autocorrelation.

[10] For further details and references see Vandebussche *et al*. (2006).

endogeneity and collinearity arising in a club convergence analysis. This strategy allows to introduce technological characteristics and institutions, captured through the identification of clubs, and spillovers connected to geographical distance modeled in terms of spatial dependence effects.
Our results strongly support TFP heterogeneity across OECD countries in the 1965-2004 period and provide evidence for a central role of human capital in the growth process.
It has been possible to identify two regimes for OECD countries. Clubs identification seems to be influenced by the quality of institutions and human capital. The convergence process is different across regimes, each characterized by important threshold externalities and different returns on physical capital accumulation, human capital stocks and technological spillovers. The key role of non linearities (interaction terms, threshold externalities) has been confirmed. The speed of convergence toward higher GDP levels can be accelerated by investing in education. Since returns on education are heterogeneous, new investment should be tailored to country's characteristics and stages of development. The key role of human capital in the imitation process has been confirmed for the club less close to the technological frontier: education may facilitate the assimilation of foreign technology in followers countries. Our analysis has shown the presence of spatial lag dependence. The global externalities are not associated with random shocks, but neighbors' income tend to positively influence the economic performance of a country.
In testing the role of human capital in a club convergence perspective, two elements of novelty have been introduced.
First, with respect to the estimation procedure, several advantages can be pointed out. The maximum entropy-based estimator is more efficient than traditional estimators, in particular when data constraints are included in the maximum entropy-based problem formulations. This procedure is able to produce estimates for models where the number of parameters exceeds the number of data points and in models characterized by a non-scalar identity covariance matrix. Prior information can be introduced by adding suitable constraints in the formulation without imposing strong distributional assumptions.
Second, looking at the role of human capital, its composition arises as a very important factor influencing the growth pattern of a country and its return is shown to be heterogeneous across clubs. Primary education has higher effects in countries less close to the technological frontier, while returns on secondary average years of schooling are greater in leading economies. With reference to tertiary schooling, high skilled workers produce negative effects in followers countries, therefore countries involved to a lesser extent in innovation activities. In these countries, investment in high education is not coupled with (sufficient) innovation activities to achieve the technological frontier. Therefore signaling and rent-seeking strategies are more likely to influence high skilled worker allocation across sectors, turning them away from R&D intensive ones. However, the positive effects of primary and (to a smaller extent) secondary education indicate the presence of effective imitation processes.
From a normative perspective, our findings provide evidence for a central role of human capital stocks in the growth process, both in levels and in terms of composition. The speed of convergence toward higher income levels can be accelerated by investing in education. Returns on education are heterogeneous therefore new investment should be tailored to the country characteristics. High level education can produce positive effects provided that such labor resources are allocated in R&D intensive sectors and the proximity to the technological frontier is guaranteed. Education may also facilitate the assimilation of foreign technology in followers countries.

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Annex

Table 1: Pooled OLS estimates

Variables	*Estimation results*	*Tests (p-values)*	
ln y_{it-1}	0.784***	*Tests for heteroskedasticity:*	
ndx_{it-1}	-0.078	1) Breusch-Pagan test	8.59 (0.003)
sk_{it-1}	0.060**	2) White test°°	138 (0.46)
Education primary	-0.370	*Tests for normality:*	
Education secondary	-0.400	1) Skewness and kurtosis of residuals°	1.02 (0.386)
Education tertiary	0.266	2) Information Matrix test	
Financial development	0.371**	- Skewness°°	32.32 (0.029)
Openness	0.024*	- Kurtosis°°	6.38 (0.012)
Fiscal expenditure	-0.022		
Inflation	0.524***	Autocorrelation of residuals°°°	
		- Lag 1	3.76 (0.0002)
*Edu tert * Fin dev*	0.214***	- Lag 2	1.31 (0.192)
*Lagged dep var * edu prim*	0.041	- Lag 3	0.11 (0.909)
*Lagged dep var * edu sec*	0.042		
*Lagged dep var * edu tert*	-0.020		
Rate of convergence	VARIABLE		
Adj. R^2	0.9845		
RMSE	0.0546		
AIC	-392.71		
BIC	-334.17		
N. obs.	138		

°Skewness and kurtosis K-square test for normality
°° Tests obtained from the Information Matrix
°°°Arellano-Bond (1991) test for autocorrelation

***1%, ** 5%, * 10% significant coefficients

Table 2: Step I GME estimates, OECD countries (1965-2004)

Variables	*Coefficient*	*Std. Error*
ln $y_{it\text{-}1}$	0.825***	0.000002
$ndx_{it\text{-}1}$	-0.008***	0.00003
$sk_{it\text{-}1}$	0.004***	0.00004
Education primary	0.167***	0.002
Education secondary	0.026***	0.003
Education tertiary	-0.002**	0.001
Financial development	-0.007***	0.001
Openness	0.004***	0.0001
Fiscal expenditure	0.016***	0.0001
Inflation	0.001***	0.0002
*Edu tert * Fin dev*	0.004***	0.001
*Lagged dep var * edu prim*	0.018***	0.0002
*Lagged dep var * edu sec*	0.002***	0.0003
*Lagged dep var * edu tert*	-0.0004***	0.0001
Spatial dep. variable	0.103***	0.001
Spatial error	0.00003***	0.00001
Rate of convergence	VARIABLE	
Adj. R^2	0.9639	
RMSE	0.0684	
N. obs.	138	

***1% significant level; **5% significant level; *10% significant level

Table 3: OECD country groupings

Club 1	AUT	**Club 2**	AUS
	BEL		CHE
	CAN		ESP
	DNK		ITA
	FIN		KOR
	FRA		MEX
	GBR		PRT
	GER		TUR
	GRC		
	IRL		
	JPN		
	NLD		
	NOR		
	SWE		
	USA		

Table 4: Step II GME estimates, OECD countries (1965-2004)

Variables	Club 1 *Coefficient*	Club 1 *Std. Error*	Club 2 *Coefficient*	Club 2 *Std. Error*
ln y_{it-1}	0.964***	0.001	0.855***	0.001
ndx_{it-1}	-0.021***	0.0003	-0.040***	0.0002
sk_{it-1}	0.002***	0.00002	0.020***	0.0001
Education primary	0.059***	0.001	0.314***	0.001
Education secondary	0.015***	0.004	0.006**	0.003
Education tertiary	-0.003	0.003	-0.019***	0.001
Financial development	-0.002***	0.0002	-0.055***	0.007
Openness	0.001***	0.00004	0.009***	0.00003
Fiscal expenditure	0.010***	0.0001	0.009***	0.0001
Inflation	0.0004***	0.0001	0.001***	0.0001
*Edu tert * Fin dev*	0.0004	0.001	0.032***	0.005
*Lagged depvar * edu prim*	0.008***	0.0002	0.026***	0.0003
*Lagged depvar * edu sec*	0.001***	0.0003	-0.000001	0.0002
*Lagged depvar * edu tert*	-0.0004*	0.0002	-0.001***	0.00004
Spatial dep. variable	0.004***	0.0001	0.007***	0.00004

***1% significant level; **5% significant level; *10% significant level