



UNIVERSITÀ POLITECNICA DELLE MARCHE

DIPARTIMENTO DI ECONOMIA

**REGIONAL CONVERGENCE, STRUCTURAL
FUNDS AND THE ROLE OF AGRICULTURE
IN THE EU**

A PANEL-DATA APPROACH

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QUADERNO DI RICERCA n. 220

Ottobre 2004

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di Stefania Bussoletti e Roberto Esposti*

Abstract

This article investigates the impact of structural funds expenditure on EU regions by estimating a conditional convergence econometric model. According to this model, regional convergence is affected by both the policy treatment and the regional economic structure proxied by the agriculture employment share, which affects regional steady state level by influencing its aggregate productivity. The convergence model is specified in a dynamic panel-data form on a dataset of 206 NUTS II EU15 regions observed over more than 10 years (from 1989 to 2000). A GMM estimation is applied to obtain consistent estimates of both the β parameter and the impact of the regional policies and agriculture employment share.

Keywords: Regional Convergence, Structural Funds, Agriculture Employment, Panel-data, GMM Estimation.

J.E.L. Classification: R110, Q100, O130, R580

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The authors are listed alphabetically and authorship may be attributed as follows: sections 1, 3, 5 to Bussoletti, sections 2, 4, 6 to Esposti. We are grateful to Pierpaolo Pierani for his precious suggestions on the estimation procedures and to an anonymous referee for remarks and suggestions on a previous version of the paper.

Contents

1. Introduction	1
2. Convergence theory, regional development and economic structure	2
2.1. <i>Conditional β-convergence and policy treatment</i>	3
2.2. <i>The role of agriculture</i>	8
3. Previous studies and data description	11
4. The estimated model	13
5. Results	18
6. Some final remarks	22
References	28

1. Introduction

This article aims to identify the impact of the European Union (EU) structural funds expenditure in Objective 1 regions; that is, policy measures specifically delivered to those regions whose *per capita* (hereafter p.c.) income is lower than 75% of the EU average. More specifically, we assume that structural payments may condition the “natural” convergence process of the poorer European regions towards the average. Therefore, we estimate an augmented conditional regional convergence model to assess if convergence is actually observed over the whole 1989-2000 period, and if structural payments significantly affected it. In addition, we allow the convergence process to be also conditioned on the regional economic structure. In particular, our interest is on assessing if the share of agriculture in the regional economy plays some role, *ceteris paribus*, i.e. with the same level of structural funds payments.

Many objective 1 regions are actually characterised by an high share of agricultural employment, though this share may greatly differ across countries and regions, especially in Southern Europe. Besides structural funds, these regions thus also receive an additional EU support from Common Agricultural Policy (CAP), still about 40% of the whole EU budget. If an higher share of agriculture negatively affects regional growth patterns and the CAP support tends to maintain somehow higher agricultural share within the regional economy, this support might eventually counterbalance the alleged growth-enhancing effect of objective 1 payments. In other words, and paradoxically, under these hypotheses CAP measures may act as a counter-treatment in objective 1 regions. Therefore, two are the basic hypotheses under study: regional structural funds may affect regional convergence process but an higher presence of agricultural activities may actually counterbalance it.

A data set of more than 200 NUTS II EU15 regions observed over about 10 years

allows to specify the convergence model in the dynamic panel-data form. The dynamic model is estimated by an appropriate GMM estimator. Alternative GMM estimates are also proposed and discussed.

2. Convergence theory, regional development policy and economic structure

In the last two decades, a significant and increasing amount of empirical studies about regional growth patterns have been based (explicitly or not) on the so-called convergence theory (Islam, 2003). Actually, the first empirical convergence analysis due to Baumol (1986) relied, in general terms, on the neoclassical growth model under the assumption that any economy could benefit from the same technological level and growth, thus achieving the same steady-state p.c. output level and growth rate. However, the actual empirical specification of the convergence model was not explicitly derived from this theoretical basis. It was “simply” a linear regression linking the p.c. income growth to its initial level as the only independent variable (this is the so-called *unconditional convergence* model).

Subsequent works added some other conditioning factors to this linear regression specification. Though these works may be now interpreted as first attempts to estimate *conditional convergence* models, they still used substantially *ad hoc* specifications, not strictly derived from the alleged underlying neoclassical growth model. This empirical strategy is what is now known as “informal” or “extensive” specification of the growth convergence model (Islam, 2003).

In 1992 two seminal empirical works by Barro and Sala-i-Martin (1992) and Mankiw *et al.* (1992), derived this linear regression specification rigorously from the transition dynamics of the neoclassical growth model (in both Solow-Swan and Cass-Koopmans versions). This is the “formal” or “model-based” specification of the growth convergence

model. It still links the p.c. income growth to the initial income level, but other conditioning variables are added and they are strictly and exclusively justified by the underlying theoretical framework.

The underlying theoretical foundation of convergence models encountered strong criticism by relatively new streams of growth literature, either the so called endogenous growth theory and the so called new economy geography (Islam, 2003). This criticism may also explain why, in many recent empirical works frequently concerning the regional context, the selection of the conditioning variables often remains conjectural (Sala-i-Martin, 1997) and why the so called “informal” convergence models are often interpreted as general empirical attempts to assess some stylised facts of growth, rather than to formally test a clear-cut growth theory.

A clear major drawback of this model-based approach is that it can not take explicitly into account the role of regional economic structure, since it is grounded on one-sector growth models. It has been widely demonstrated that the change in sectoral shares in the regional economy is a major factor affecting the regional growth pattern (Bernard and Jones, 1996). However, although the “formal” convergence model does not allow sectoral composition to surface directly, this still evidently affects, directly or not, several conditioning variables and structural parameters. Recent studies on USA rural counties demonstrated, within a growth convergence framework, that an higher level of local dependence on agriculture may lower regional growth rates, *ceteris paribus* (Deller *et al.*, 2003). This article aims to further investigate this aspect with respect to EU regions.

2.1. Conditional β -convergence and policy treatment

In policy impact analysis one major interest is to assess if the policy measures (hereafter “the treatment”) affect somehow this regional growth convergence pattern.

However, most empirical works trying to assess the effect of regional policies on growth seem to revert back to the original informal specification, as major difficulties are encountered in giving them a stronger theoretical justification, that is, in consistently including the policy measure as conditioning variable in the model-based conditional convergence process.

When formally derived from the neoclassical growth theory, the model-based conditional β -convergence¹ model can be expanded as follows (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1995):

(1)

$$E(y_{it}|Y_{i0}, T_i = 0, X_{i0}) = t g + (1 - e^{-\lambda t}) \ln A_{i0} + (1 - e^{-\lambda t}) \frac{\alpha}{1-\alpha} \ln s_{i0} - (1 - e^{-\lambda t}) \frac{\alpha}{1-\alpha} \ln(n_{i0} + g + \delta) - (1 - e^{-\lambda t}) \ln Y_{i0}$$

where, on the left-hand side, y_{it} is the i -th region p.c. income growth rate over period t , Y_{i0} indicates the i -th region initial (at time 0) p.c. income, X_{i0} is a set of other conditioning variables and $T_i=0$ indicates that no policy (no treatment) has been delivered to the i -th region during the period. The whole set of conditioning variables is made explicit on the right-and side where g is the total factor productivity growth rate, λ is the speed (or rate) of convergence, A_{i0} is the i -th region initial total factor productivity, α is the coefficient of the underlying Cobb-Douglas production function (indicating the rate of technical substitution between capital and labour, i.e. the capital's share within the economy or capital intensity), s_{i0} is the i -th region initial investment rate, n_{i0} is the i -th region initial population (or workforce) growth rate, δ is the capital depreciation rate.

g , δ and α are assumed constant across regions and over time. This is implied by the underlying growth model but can be relaxed within endogenous growth models, and also in

¹ Besides the concept of β -convergence, the idea of σ -convergence has been proposed (Barro and Sala-I-Martin, 1992; Quah, 1996). Whereas the former tries to model the expected value of income growth conditional on initial value, the latter models its statistical distribution across regions, over

the extensive version of the model with human capital proposed by Mankiw *et al.* (1992). However, relaxing these assumptions would make the concept itself of growth convergence inherently ambiguous (Islam, 2003).

Equation (1) establishes on a theoretical ground the vector of the conditioning variables, as we can write $X_{i0} = (A_{i0} \ s_{i0} \ n_{i0})$, while g , δ and α are structural parameters. Equation (1) also expresses the regional convergence process toward its own steady-state growth rate. This is also formulated as the steady-state output per unit of effective labour, Y^* ; that is, in log terms (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1995):

$$(2) \quad \ln Y^* = \frac{\alpha}{1-\alpha} [\ln s_{i0} - \ln(n_{i0} + g + \delta)]$$

The conditioning variables s_i and n_i are supposed to be constant over time and exogenous, therefore equal to the respective values computed at time 0 in equation (1). Different s and n across regions imply different regional steady-states and, therefore, “parallel” convergence patterns. Apparently, the initial total factor productivity A_{i0} does not affect the steady-state output level. However, if we derive from (2) the steady-state output per unit of actual labour, \hat{Y}_t , we obtain:

$$(2b) \quad \ln \hat{Y}_t = t g + \ln A_{i0} + \frac{\alpha}{1-\alpha} [\ln s_{i0} - \ln(n_{i0} + g + \delta)]$$

This equation makes explicit that the steady-state growth of output per labour unit (or *per capita*) is only generated by the total factor productivity growth rate, while the level of this output is determined also by the other conditioning variables in X_{i0} .

When all these conditioning variables are equal across the observations (regions), we have an conventional unconditional β -convergence model, that is:

$$(3) \quad E(y_{it} | Y_{i0}, T_i = 0, X_{i0}) = a + \beta \ln Y_{i0}$$

time or both. Although β -convergence is a necessary condition to have σ -convergence, convergence

where:

$$a = t g + (1 - e^{-\lambda t}) \ln A_0 + (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln s_0 - (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln (n_0 + g + \delta)$$

$$\beta = - (1 - e^{-\lambda t})$$

Therefore, so-called “informal” unconditional convergence models can be viewed as a reduced form of the structural model in (1).

On the contrary, we have conditional convergence, and different steady-states, if regions differ in terms of initial technology, investment rate and population growth. These variables (or some appropriate proxy of them) are the only legitimate conditioning variables in a neoclassical model-based conditional convergence model. By substituting equation (2b) in equation (1), we can rewrite the convergence model as follows:

$$(1b) \quad E(y_{it} | Y_{i0}, T_i = 0, X_{i0}) = e^{-\lambda t} t g + (1 - e^{-\lambda t}) (\ln \hat{Y}_t) - (1 - e^{-\lambda t}) \ln Y_{i0}$$

which clearly indicates that the observed regional growth pattern depends on the initial per unit output level, its own steady-state level, its rate of convergence and the exogenous technical change rate (that is the steady state growth rate).

The empirical identification of all structural parameters of equation (1) is not an easy task. Many empirical works still estimate the “reduced” version of the convergence model, with the initial income and other variables as regressors. The estimation of the reduced form has been criticized by some authors (Islam, 2003), since it disregards the underlying relations and constraints between the estimated reduced-form parameters and the structural growth-model parameters.

Here, the main issue is just how to include the treatment in the structural convergence model above. We can measure the treatment as a weighted sum of past policy expenditure

may be observed according to the first concept but not in distributional terms.

within the region, that is $T_i = \sum_{s=0}^Z w_s M_{it-s}$, where w_s is the weight indicating the “portion” of the policy measure (expenditure) M delivered at time $t-s$ affecting the outcome at time t . Objective 1 expenditures can be prevalently considered as investments, since 98% of objective 1 funds concentrates on three main areas: infrastructure, human capital, support to other (mainly private) investments (Bussoletti, 2004; European Commission, 2004). Consequently, the more natural way to include this treatment in the model-based conditional convergence model, is to assume the following relation between the regional investment rate s and the past treatment:

$$(4) \ln s_{i0} = \gamma + \phi \sum_{s=-Z}^0 w_s M_{is}$$

The growth convergence model conditional on the treatment thus becomes:

$$(5) E\left(y_{it} \mid Y_{i0}, T_i = \sum_{s=-Z}^0 w_s M_{is}\right) = a + \phi \sum_{s=-Z}^0 w_s M_{is} + \beta \ln Y_{i0}$$

where:

$$a = t g + (1 - e^{-\lambda t}) \ln A_0 + (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \gamma - (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln(n_0 + g + \delta)$$

$$\phi = (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \phi$$

Equation (5) remains a “reduced” from model, but now the treatment is consistently grounded on the growth model and it allows measuring the expected value of the respective treatment effect on the i -th region (TE_i) as follows:

$$(6) TE_i = E\left(y_{it} \mid Y_{i0}, T_i = \sum_{s=-Z}^0 w_s M_{is}\right) - E(y_{it} \mid Y_{i0}, T_i = 0) = \phi \sum_{s=-Z}^0 w_s M_{is}$$

where ϕ is expected to be positive for the policy to be effective.

2.2. The role of agriculture

In this study we admit that total factor productivity may differ across sectors; thus, we implicitly admit that this conditioning variable depends on the regional economy structure as its regional aggregate value will be function of the sector shares themselves. Islam (2003) acknowledges that in many empirical works the regional initial total factor productivity A_{i0} is expressed as function of some structural variable, for instance the share of some key-sector. Since objective 1 regions generally show much greater agricultural share than the EU average (as shown in figure 1), it may be reasonable for our purposes to assume that this initial technological level depends on the regional share of agriculture, AG_{i0} (expressed as % of agriculture on total regional employment). For simplicity, we assume the following linear relationship:

$$(7) \quad \ln A_{i0} = \kappa + \psi AG_{i0}$$

the hypothesis being that agriculture has a lower total factor productivity with respect to other sectors and, therefore, the higher is its share the lower the initial overall regional productivity. Thus, ψ is expected to be negative. By substituting in equations (1) and (5) we can rewrite the convergence model in reduced form as follows:

$$(8) \quad E \left(y_{it} \left| Y_{i0}, T_i = \sum_{s=-Z}^0 w_s M_{is}, AG_{i0} \right. \right) = a + \varphi \sum_{s=-Z}^0 w_s M_{is} + \xi AG_{i0} + \beta \ln Y_{i0}$$

where:

$$a = t g + (1 - e^{-\lambda t}) \kappa + (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \gamma - (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln(n_0 + g + \delta)$$

$$\xi = (1 - e^{-\lambda t}) \psi$$

According to equation (8), β -convergence is now conditioned on two variables: the treatment and the initial sectoral structure. The estimation of equation (8) provides the reduced-form parameters a , β , φ , ξ . Anyway, it is also possible to derive implicitly the

structural parameters, and mainly α . In fact, currently available EU regional data provide also comparable regional initial population (or workforce) growth rate n_{i0} ; moreover, although regional observations on δ and g are lacking, many empirical works make assumptions about the common value of the $(\delta + g)$ term. Mankiw *et al.* (1992) assume $(\delta + g) = 0,05$, and we follow the same assumption.² Therefore, the $\ln(n_0 + g + \delta)$ term may be considered as region-specific. In addition, panel-data specifications allow to consider the constant term itself as region-specific. It follows that the regional convergence model can be specified as follows:

$$(9) \quad E\left(y_{it} \mid Y_{i0}, T_i = \sum_{s=-Z}^0 w_s M_{is}, AG_{i0}, n_{i0}\right) = a_i + \varphi \sum_{s=-Z}^0 w_s M_{is} + \xi AG_{i0} + \beta \ln Y_{i0} + \chi \ln(n_{i0} + g + \delta)$$

where:

$$a_i = t g + (1 - e^{-\lambda t}) \kappa_i + (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \gamma_i$$

$$\chi = - (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha}$$

The region specific a_i terms thus represent a further conditioning variable since they affect the region-specific steady state level.³

Equation (9) remains a “reduced” model since some underlying structural parameters can not be directly estimated. Nevertheless, they can be indirectly obtained through the estimated reduced-form parameters by substituting in equations (2), (4) and (7). The following identities hold:

$$\lambda = - \frac{\ln(\beta + 1)}{t}$$

$$\alpha = \frac{\chi}{\beta + \chi}$$

² Badinger *et al.* (2002) assume a much higher value (0,25). However, in the present case different values of this term does not particularly affect the estimation results.

³ As will be introduced in the fourth section, the region-specific constant term may be alternatively assumed to be random.

$$\phi = -\frac{\varphi}{\chi}$$

$$\psi = -\frac{\xi}{\beta}$$

Finally, from equations (4) and (7) it is also possible to express the impact of the structural funds payments and of the agriculture employment share in terms of elasticity as follows:

$$\varepsilon_{s,M}^i = \frac{\partial \ln s_{i0}}{\partial \ln M_{is}} = \phi M_{is}$$

$$\varepsilon_{A_0,AG}^i = \frac{\partial \ln A_{i0}}{\partial \ln AG_{i0}} = \psi AG_{i0}$$

which also leads to the elasticities expressing how, through s_{i0} and A_{i0} , they actually affect the steady-state p.c. output growth rate according to equation (2b)⁴:

$$\varepsilon_{\hat{Y},M}^i = \frac{\partial \ln \hat{Y}}{\partial \ln M_{is}} = \frac{\alpha}{1-\alpha} \phi M_{is}$$

$$\varepsilon_{\hat{Y},AG}^i = \frac{\partial \ln \hat{Y}}{\partial \ln AG_{i0}} = \psi AG_{i0} = \varepsilon_{A_0,AG}^i$$

In the convergence model in equation (9) any region is allowed to “follow” its own steady state growth pattern, as indicated by the estimated reduced-form parameters. In particular, β allows to assess whether convergence occurs or not and which is the speed (since λ can be easily derived); χ , φ and ξ indicates whether convergence is conditional or not. φ demonstrates if the treatment has an effect and which is the magnitude of this effect; ξ if the sectoral structure matters.

Moreover, the region-specific (constant) parameters behave themselves as conditioning variables since they affect the regional investment rate and productivity. In particular, the two variables of major interest here, structural policy and the agriculture share,

⁴ The assumption is made that s_i remains constant, if not shocked by M , and its observed initial level

conditions the convergence pattern along two different underlying processes: while structural funds are assumed to affect the capital deepening process, the share of agriculture (and, more generally, the regional sectoral composition) affects the technological level.

These two processes may also counter-balance. If agriculture share really determines a lower steady state thus reducing, *ceteris paribus*, the regional growth rate, this would support the idea that any policy eventually maintaining higher agricultural share, actually induces a sort of counter-treatment with respect to objective 1 funds. Past policies that supported agriculture in such a way to maintain relatively high employment levels in the sector, may actually reduce the impact of successive objective 1 structural funds payments.⁵

3. Previous studies and data description

Objective 1 treatment started in 1989 and involves a relevant part of the European Union: currently, about 50 regions, 20% of the population, i.e. 70 millions of inhabitants. The EU spends between 20% and 25% of its annual budget on structural funds for objective 1 regions, which means about 0,25% of the whole EU GDP (European Commission, 2004). Nevertheless, the size of the divergence remains so relevant in absolute terms to motivate serious doubts on the presence of any real convergence process within the Union and about the actual capacity of this financial effort to significantly affect it.

Previous empirical estimates of the regional convergence within the EU provide mixed and controversial results. This may be motivated by the “confusion” generated by a large amount of different model specifications, data and econometric methods used in this literature. First cross-sectional regional studies by Barro and Sala-i-Martin (1991) and Sala-i-

corresponds to the steady-state level.

⁵ The idea behind this hypothesis is that past Common Agricultural Policy (CAP) support might have generated this counter-treatment effect in some objective 1 regions. However, since long time series about regionalised CAP payments in the whole EU are not available, this hypothesis can not be explicitly tested by including these payments as “additional” treatment within the

Martin (1996) suggest unconditional regional convergence both in the EU and in the USA, at an annual convergence speed of about 2%. Croci Angelini (2002) surveys 16 different estimates of unconditional convergence across the EU published from 1992 to 2000; the unconditional convergence rates vary between 0,4% and 2,9%; indeed, however, several studies actually provide evidence against the regional β -convergence in the EU (Abraham and Van Rompuy, 1995; Molle and Boeckhout, 1995).

Very different results, particularly in terms of convergence speed, are obtained when a panel and dynamic specification is used. Canova and Marcet (1995) report a very high (about 11% for the EU countries, 23% for the regions) convergence speed. On the opposite side, there is an increasing number of recent panel-data not showing any clear evidence of unconditional convergence across EU countries and, above all, regions (Boldrin and Canova, 2001). Conditional convergence is strongly supported by some empirical works (Fagerberg and Verspagen, 1996; Neven and Gouyette, 1995), while contested by others. Moreover, several recent empirical studies are increasingly corroborating the so-called club-convergence, that is convergence observed within subgroups of regions (Chatterji, 1993; Canova, 1999; Quah, 1996).⁶

Despite this huge amount of empirical literature, there is far less abundance of empirical analyses about regional convergence conditional on objective 1 payments and the role of sectoral composition. In a recent publication, the EU Commission (European Commission, 2004) reports an unconditional convergence rate over all EU regions of 0,5% for the 1980-1988 period; this rates increases to 0,7% and 0,9% in the periods 1989-1993 and 1994-2000, respectively. During these two structural funds programming period, convergence

convergence model.

⁶ Distinguishing between conditional and club convergence may be indeed difficult (Islam, 2003). Club convergence is, in fact, a particular case of conditional convergence. The latter implies an individual regional-specific steady-state level, whereas club convergence implies multiple steady-state equilibria, one for any group (club) of regions.

rate observed across objective 1 regions has been 3,1% and 1,6%. Unfortunately, none of this evidence is sufficient to demonstrate a positive conditioning impact of structural funds in this convergence process.

In this article, income, population and other economic data about NUTS II EU15 regions are taken from the Newcronos Regio database (Eurostat); income data are expressed in Purchasing Power Standard (PPS) currency.⁷ The EU15 database thus obtained covers all the 206 EU15 NUTS II regions over the whole 1989-2000 period.⁸ Data about structural funds in objective 1 regions refer to annual expenditure in the two programming periods 1989-1993 and 1994-1999. To have an overall computation of the expenditure, all structural funds payments are considered (ERDF, which is the main contributor to objective 1 programme, ESF, EAGGF and FIFG). Unfortunately, there is not an unique centralised database about structural funds expenditure at the regional level. Therefore, this has been created on the base of the information provided by the European Commission Annual Reports on structural funds payments and considering both regional and multiregional programmes.⁹

All objective 1 payments here considered are expressed in PPS, by using the same conversion index used by the EUROSTAT for converting the regional income in the common comparable currency.

4. The estimated model

The regional conditional convergence model in equation (9) is estimated for the whole

⁷ This virtual currency converts all national currencies to the common European currency (Ecu-Euro) and then adjusts for the different purchasing power within the countries.

⁸ Current NUTS classification actually contains 211 NUTS II regions. However, due to data availability, Ireland is included as one NUTS II region as well as NUTS I German regions Sachsen and Sachsen-Anhalt.

⁹ Extensive information on data sources and treatment can be found in Bussoletti (2004).

1989-2000 period.¹⁰ The model is applied to all the 206 EU15 regions. The dynamic panel-data specification of the convergence model is becoming increasingly popular in the empirical literature (Carmeci and Mauro, 2002; Caselli *et al.*, 1996; Yudong and Weeks, 2000). The simplest dynamic version is an AR(1) model as follows¹¹:

$$(10) \quad y_{it} = a + \rho y_{it-1} + \varphi T_i + \xi AG_{it-1} + \beta \ln Y_{it-1} + \chi \ln(n_{it-1} + g + \delta) + \varepsilon_{it}$$

where the variables definition has been already presented in section 2; ρ is the first-order autocorrelation coefficient. T_i indicates the regional treatment affecting i-th region growth and is specified here in two different ways. Firstly as a simple dummy identifying the treatment status at time t-1 (0 if non-treated, 1 if treated). Secondly, as treatment intensity

$$T_i = \sum_{s=0}^{-2} 0,33 M_{it-s},$$

that is the three years (two years for 2000) average *per capita* expenditure

(M_{it}) also to mitigate the relevant variation usually observed over the *year per year* expenditure.

The error term of equation (10) contains the region-specific effect being defined as follows:

$$(11) \quad \varepsilon_{it} = \mu_i + \nu_{it}$$

In other words, the error term contains a time-costant and a time-varying component but both varying over the *cross section* dimension. If the individual effect is assumed to be fixed (non-random), it follows:

$$(11b) \quad \varepsilon_{it} = \mu_i + \nu_{it} \Rightarrow \sigma(\varepsilon_{it}) = \sigma_\nu$$

¹⁰ The year 2000 is included in the sample period to take into account the effect on growth of the last year of payments (1999). Although regional data about structural funds expenditure (still referring to the 1994-1999 period) are available also for 2000, this year is considered off-treatment because these expenditure data are incomplete and unreliable. This implies that, though year 2000 is included in the sample, it is affected only by 1999 and 1998 payments.

¹¹ Due to the limited time period, only one lag of the dependent variable has been considered here in the dynamic specification.

and the constant term now becomes $a_i = (a + \mu_i)$ as in equation (9), i.e. region-specific. Alternatively, a random region-specific effect may be assumed, with $E(\mu_i)=0$ and $\sigma(\mu_i)=\sigma_i$. It follows:

$$(11c) \quad \varepsilon_{it} = \mu_i + v_{it} \Rightarrow E(\varepsilon_{it}) = E(\mu_i) + E(v_{it}) = 0; \quad \sigma(\varepsilon_{it}) = \sigma_v + \sigma_i + E(\mu_i v_{it})$$

Under random effects, even assuming $E(\mu_i v_{it})=0$, the variance-covariance matrix of the error term (Σ) is not diagonal, that is $\Sigma \neq \sigma^2 I$.

We could let the data choose between the fixed and random effects specifications. However, Islam (2003) underlines that the random effects specification should be excluded under the neoclassical growth framework, as it implies that individual effects are correlated with some regressors (expected to be exogenous), since both contains the same parameters and variables of the underlying regional growth pattern. At least in principle, this would generate biased estimates (endogeneity bias). As there is clear theoretical justification, we only consider the fixed effects version of the dynamic model in equation (10).¹²

This dynamic specification explicitly takes into account the serial correlation, which often affects income growth. Disregarding this aspect would make estimates inconsistent due to the omitted variable bias. However, introducing the lagged values of the dependent variable eventually implies that the i.i.d hypothesis of the v_{it} term over time does not hold anymore, as it is correlated with the lagged dependent variable (Arellano, 2003). In other words, y_{it-1} is endogenous.

Thus, an instrumental variable estimator must be used to achieve consistent estimates of parameters in equation (10). Here, we use a GMM estimator. Firstly, the GMM estimator proposed by Arellano and Bond (1991) is adopted. This implies rewriting equation (10) in the

¹² A previous paper using an analogous regional sample and period (Bussoletti and Esposti, 2004) empirically tested (with a conventional Hausman test) the fixed effects vs. the random effects

first-differences (GMM-DIFF estimator), as this generates a first differenced error term $\Delta\varepsilon_{it}$ which is uncorrelated with any lagged level variable y_{it-s} ($\forall s \geq 2$). These lagged variables are thus legitimate candidate as valid instruments according to the moment (orthogonality) condition $E[\Delta\varepsilon_{it} y_{it-s}] = 0$. Both the one-step and two-steps GMM estimators proposed by Arellano and Bond (1991) are adopted here. Although both are consistent, the latter provides asymptotically efficient estimates. Nevertheless, several empirical applications suggest that, in finite samples, the two-steps estimator may actually generate little, if any, efficiency improvement while the one-step estimator may also outperform the two-steps counterpart in terms of robustness (Blundell and Bond, 1998; Carmeci and Mauro, 2002, 2003; Gaduh, 2002; Judson and Owen, 1999).

The asymptotic properties of the Arellano and Bond (1991) GMM estimators may be counterbalanced by poor performances in finite samples: Blundell and Bond (1998) show that these estimators may incur relevant small sample bias and the precision of the estimates tends to decrease in AR(1) specifications, whenever the autocorrelation coefficient is close to 1. For this reason (also known as weak instruments problem) the lagged levels may be poor instruments in first difference equations. Blundell and Bond (1998) suggest an alternative system GMM estimator (GMM-SYS), where a system of equations is estimated by adding equations in levels to first difference equations. Under a mean stationary AR(1) process, the lagged first difference Δy_{it-1} is uncorrelated with ε_{it} , so can be used as valid instrument for the respective level equation, according to the moment condition $E[\varepsilon_{it} \Delta y_{it-1}] = 0$.

The finite sample performance improvement provided by the GMM-SYS estimators is also questioned by some empirical applications where GMM-DIFF estimates appear to be more robust especially with small sample size and when the two-steps procedure is followed

specification of the model, thus confirming that the fixed effects model has to be accepted.

(Lucchetti *et al.*, 2001). More generally, it is often concluded that no single estimator of dynamic panel models can appear to be superior in all circumstances (Badinger *et al.*, 2002). Nevertheless, in the recent growth convergence literature, the GMM-SYS estimator provided more modest, and realistic, rates of convergence, ranging from 2 to 4% per annum, quite close to most cross-section studies.¹³ In the present application, since there is no clear indication about which estimator should be preferred in case of small sample size, we provide results of all the mentioned estimators and the comparison among them may be particularly informative.

A major issue concerning the application of the GMM estimators is the selection of the instrumental variables. In this article, all available and admitted lagged income growth variables are considered. We also include the out-sample observations; that is, the annual income growth rates observed in the period 1980-1988 have been admitted as candidate instruments. To assess the consistency of the instruments selection, an overidentifying restriction (Sargan) test is adopted (Arellano, 2003).¹⁴ Under the null hypothesis, this test assumes that all the selected instruments are valid, i.e. exogenous. The rejection of the null would thus indicate an inappropriate selection of the instrumental variables. Problems may also derive from the incorrect specification of the dynamic structure of the model, and this requires testing for the serial correlation of the differentiated error terms. Here, we adopt the first and second order serial correlation LM tests proposed by Arellano and Bond (1991).¹⁵ If the AR(1) specification is valid, we should observe first order correlation (generated by first-differentiation) but no second order correlation.

¹³ Bond *et al.* (2001) obtain a 2,4% convergence rate with a GMM-SYS estimator using the same data set and model specifications adopted by Caselli *et al.* (1996) and that reported a 13% GMM-DIFF estimate.

¹⁴ This statistic is distributed as chi-square under the null of all instruments orthogonal to the respective error terms and with degrees of freedom given by the difference between the number of moment conditions and of unknown parameters.

¹⁵ Both statistics are distributed as standard normal under the null of no serial correlation.

5. Results

Tables 1 and 2 report the GMM estimates of the dynamic model (equation (10)). Results are presented through a sequence of different specifications: starting from the unconditional convergence case, the conditioning variables (population growth, the treatment and the agriculture share) are then progressively added. As mentioned, in finite samples, the dynamic model estimates raise a number of additional econometric issues, which may, indeed, mix up the results. In particular, significant differences may emerge among the four alternative GMM estimators (one-step and two-steps for GMM-DIFF and GMM-SYS, respectively). Secondly, the choice of the instrumental variables remains critical, and partially subjective, with possible remarkable impact on final results.

The first evidence concerns the autocorrelation coefficient. In all four estimates, this coefficient is quite low (less than 0,1) but statistically different from 0, with the only exception of the GMM-DIFF one-step estimator, and always positive suggesting slight persistency in growth rates and implying downward correction of the β coefficient estimate. As far from unity autocorrelation coefficient tends to exclude any risk of non-stationarity and may eventually reduce the gain obtained through the GMM-SYS estimation.

β convergence is observed across all specifications and estimators. Confirming previous evidence, the GMM-DIFF estimation of the convergence rate is higher than the GMM-SYS analogous (7,6% and 5,1% respectively), though the difference is less dramatic than observed in other studies (Bond *et al.*, 2001). The major interest in results provided by the GMM estimation concerns the role of the conditioning variables. Firstly, the GMM estimates provide clear evidence about the impact of objective 1 regions structural funds. The impact is not significant or negative when the treatment is roughly introduced as a dummy; whenever it is specified as p.c. expenditure level, it always has a positive and significant impact, though the magnitude remains small and varying according to the different estimators,

the highest being observed with the GMM-DIFF approach. This result confirms some previous studies estimating the structural funds impact on regional convergence and using similar model specification and estimation approach. In particular, Beugelsdijk and Eijffinger (2003) find similar results about the objective 1 funds, though they apply the convergence model to the EU15 countries and not, as seems more appropriate, to NUTS II regions (the actual recipients of these funds). Moreover, they specify the treatment as structural payment growth rate instead of payment level, as in the present application, the former apparently being much less regular and potentially more statistically “noisy” over a short time period.

The parameter concerning population growth (χ) is always negative, as expected, but statistically significant only in the two-steps estimation. The downward impact on the regional growth rate, however, is almost negligible in the GMM-SYS estimates, while it is much more relevant (more than 7 times higher) under GMM-DIFF. This plays also a relevant role in the calculation of the implicit structural parameters, since χ enters in the computation of α and ϕ and of the relative elasticities. Eventually, this seems to be the major difference between the GMM-DIFF and GMM-SYS estimation.

For all GMM estimators, the estimated parameter of the agriculture share on regional employment (ξ) accepts the hypothesis of a negative impact of the sector on regional growth through a negative impact on the region-specific initial total factor productivity, thus confirming the expectations and previous results on USA regions based on a similar convergence approach (Deller *et al.*, 2003). The parameter is significantly negative, though apparently almost negligible in magnitude; this suggests that there is, at least indirectly, empirical support to the possible counter-treatment effect of any measure sustaining the share of agriculture within the regional economy. Moreover, this result would suggest, somehow not surprisingly, the relevance of the regional economic structure in terms of sectoral balance. The real impact of any variation in the agriculture share on the regional growth pattern can be

shown through the respective elasticities (table 3). It must be noticed that the elasticity of A_0 with respect to the agriculture share remains quite stable over the different GMM estimates ranging from -0,150 to -0,250. Also the elasticities calculated with respect to the structural funds expenditure does not vary much ranging from 0,147 to 0,563 for the investment rate, and from 0,120 and 0,431 for the steady state p.c. output level. In general terms, parameters and respective elasticities clearly indicates that the conditioning effect on regional growth convergence pattern of the two variables is significant and goes in the expected direction, but it is quite limited in magnitude as confirmed by all GMM estimates.

It is of major interest here to assess if GMM estimates are consistent with the theoretical framework on which the estimated convergence model is grounded. Besides the statistical significance and correct sign of most of the parameters, the key evidence in this respect should come from the derivation of the implicit structural parameters. In particular, the α parameter indicates the capital intensity (i.e., the capital share) within the economy. As stressed by Islam (2003), many convergence studies do not report the implicit value of this parameter or obtain values that are clearly unreliable or even impossible. α must range between 0 and 1 and should realistically fall in the 0,30-0,50 interval. It is interesting to notice that the GMM-DIFF generates values of α quite close to this interval. In particular, if we consider the specification with all the conditioning variables, it varies between 0,41 and 0,45. On the contrary, the GMM-SYS provides less reliable values ranging from 0,17 to 0,28 in the extensive specification.

Comparing the GMM estimates, one major conclusion is that there is no evidence of any remarkable gain passing from the GMM-DIFF to the GMM-SYS estimation, both in terms of statistical significance and economic reliability. For this latter aspect it seems that, on the contrary, the GMM-DIFF results are closer to the theoretical expectations. This should not surprise too much. The GMM-SYS can dramatically improve the estimation performance

particularly under already mentioned specific conditions about either the sample and the model. They do not seem to apply in the present case.

Moreover, the choice of the appropriate instruments set may be even more critical in the GMM-SYS approach. Tables 1 and 2 also report the mentioned diagnostic statistical tests for the choice of the instrumental variables. First of all, the LM tests should support the correctness of the AR(1) specification, which also drives the choice of the instruments. As expected, for all the GMM-DIFF estimates, we reject the hypothesis of no first order serial correlation of the differentiated error terms, while we accept the hypothesis of no second order correlation. Therefore, as the AR(1) specification is accepted, the instruments can be chosen consequently. The Sargan tests confirm that the instrumental variables have been selected correctly in the GMM-DIFF case, since we can accept the hypothesis they are orthogonal with respect to the differentiated residuals.

Statistical tests provide less clear evidence for the GMM-SYS estimates; Sargan still confirms validity of the instruments but the hypothesis of no second order correlation of the differenced residuals could be rejected in some cases, suggesting problems in the dynamic specification of the model. The validity of the extra-instruments implied by the GMM-SYS estimation can be tested, by calculating the difference between the Sargan statistics obtained for the GMM-SYS and GMM-DIFF estimations. This difference is also called Difference Sargan and is asymptotically distributed as a χ^2 with degrees of freedom given by the respective difference. Considering the two-steps estimates and the specification with all conditioning variables, this statistics is 5,282 (p-value = 0,00); therefore, the validity of the extra-instruments may be accepted.

6. Some final remarks

This article attempts to estimate the impact of EU structural funds and of the regional sectoral composition on objective 1 regions growth within a growth convergence model. By adopting a dynamic panel-data specification, the estimated conditional convergence model is derived from the underlying neoclassical growth model where structural funds enter as determinant of the regional investment rate and the agriculture employment share as a proxy of the underlying regional technological level. Including these two conditioning variables in the model-based convergence model not only provides theoretical justification to the empirical application, but also allows to assess if the effect generated by the structural funds payment may be eventually counterbalanced by policies supporting low productivity sectors, as most agricultural policies.

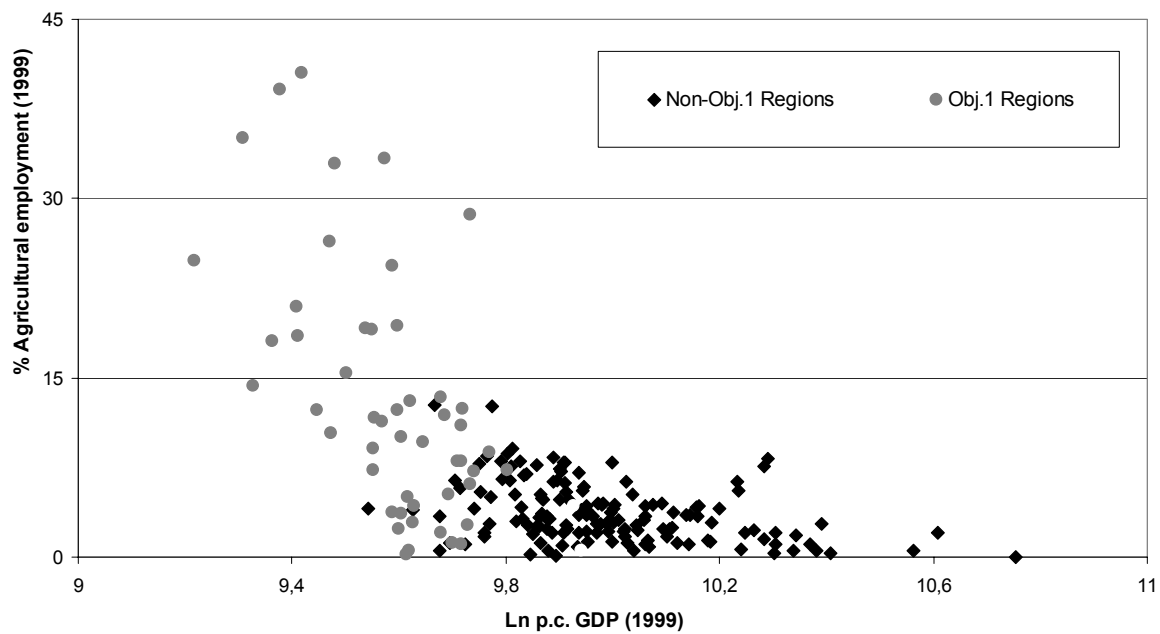
Results confirm that the dynamic specification is more appropriate in this empirical application, thus suggesting that static panel-data estimators may provide biased estimates. In general terms, and regardless the adopted estimator, growth convergence is observed. As well demonstrated in recent related literature, the convergence rate may significantly vary across alternative specifications and estimators. Here, however, this variability seems less marked, as reliable and consistent estimates of the convergence rate ranges from 5% to 7,5%, higher than what usually obtained in cross-sectional studies by 2-3%.

Among conditioning variables, a positive impact of structural funds on objective 1 regions is confirmed, though its statistical significance and magnitude may vary across alternative estimators. Similarly, the role of agriculture employment share confirms the expectations, since it negatively affects the regional growth by reducing its total factor productivity. The respective effects on the regional growth pattern seem, however, quite limited. Anyway, the results support the hypothesis that these variables may actually counterbalance: an increase (or a lower decrease) of the agriculture employment share reduces

the effect of a given amount of structural funds payments. However, to explicitly test whether EU agricultural policies really indirectly act as a counter-treatment with respect to structural funds in objective 1 regions definitely requires further evidence and research effort.

Comparing these results with previous studies about the impact of objective 1 funds reveals how relevant some apparently marginal issues may be. First of all, if the treatment is included as a dummy rather than as p.c. expenditure level, its impact on growth is rarely significant and, sometimes, even negative. Secondly, the lag structure representing the effect of funds over time is of major relevance and it is too often disregarded in empirical works on the subject. In more general and, perhaps, obvious terms, the quality of the conditional convergence model estimates critically depends on how the policy under study enters the model itself and how the respective data are treated.

Figure 1: Relation between regional agricultural employment and p.c. GDP (year 1999)



Source: Our elaboration on Regio Database - Eurostat

Table 1: GMM-DIFF one-step and two-steps estimates of the dynamic convergence model (equation (10)) (standard errors = SE below the estimated values): EU15 regions (206 observations)

Specification	ρ (SE)	β (SE)	χ (SE)	φ (SE)	ξ (SE)	Implicit Structural Parameters				Test of first-order autocorrelation (LM test)	Test of second-order autocorrelation (LM test)	Test of over-identifying restrictions (Sargan test)
						λ	α	ϕ	ψ			
One-step												
Unconditional convergence	0,032 (0,095)	-0,053 (0,011)				0,054				-4,475 (p value = 0,00)	-0,086 (p value = 0,93)	1,261 (p value = 1,00)
Treatment as dummy T=0,1	0,025 (0,091)	-0,037 (0,011)	-0,051 (0,045)	-0,047 (0,014)		0,038	0,577			-4,535 (p value = 0,00)	-1,076 (p value = 0,28)	1,223 (p value = 1,00)
Treatment as expenditure level (T = M)	0,052 (0,099)	-0,062 (0,011)	-0,067 (0,044)	$0,432 \cdot 10^{-4}$ ($0,218 \cdot 10^{-4}$)		0,064	0,520	0,001		-4,849 (p value = 0,00)	-0,385 (p value = 0,70)	1,226 (p value = 1,00)
Treatment (T = M) and agricultural employment share	0,056 (0,098)	-0,073 (0,015)	-0,051 (0,055)	$0,307 \cdot 10^{-4}$ ($0,240 \cdot 10^{-4}$)	-0,002 (0,002)	0,076	0,411	0,001	-0,051	-4,858 (p value = 0,00)	-0,410 (p value = 0,68)	1,219 (p value = 1,00)
Two-steps												
Unconditional convergence	0,035 (0,004)	-0,052 (0,001)				0,053				-4,476 (p value = 0,00)	-0,038 (p value = 0,97)	1,260 (p value = 1,00)
Treatment as dummy T=0,1	0,028 (0,005)	-0,036 (0,002)	-0,079 (0,012)	-0,046 (0,003)		0,053	0,604			-4,562 (p value = 0,00)	-1,027 (p value = 0,30)	1,217 (p value = 1,00)
Treatment as expenditure level (T = M)	0,055 (0,005)	-0,061 (0,002)	-0,073 (0,007)	$0,412 \cdot 10^{-4}$ ($0,046 \cdot 10^{-4}$)		0,063	0,540	0,001		-4,847 (p value = 0,00)	-0,381 (p value = 0,70)	1,121 (p value = 1,00)
Treatment (T = M) and agricultural employment share	0,060 (0,005)	-0,071 (0,002)	-0,058 (0,008)	$0,295 \cdot 10^{-4}$ ($0,041 \cdot 10^{-4}$)	-0,002 ($0,256 \cdot 10^{-3}$)	0,074	0,449	0,001	-0,031	-4,865 (p value = 0,00)	-0,393 (p value = 0,69)	1,119 (p value = 1,00)

Table 2: GMM-SYS one-step and two-steps estimates of the dynamic convergence model (equation (10)) (standard errors = SE below the estimated values): EU15 regions (206 observations)

Specification	ρ (SE)	β (SE)	χ (SE)	φ (SE)	ξ (SE)	Implicit Structural Parameters				Test of first-order autocorrelation (LM test)	Test of second-order autocorrelation (LM test)	Test of over-identifying restrictions (Sargan test)	
						λ	α	ϕ	ψ				
One-step													
Unconditional convergence	0,159 (0,036)	-0,003 (0,007)				0,003					-4,452 (p value = 0,00)	2,138 (p value = 0,03)	3,534 (p value = 1,00)
Treatment as dummy T=0,1	0,093 (0,041)	-0,049 (0,011)	-0,017 (0,019)	-0,001 (0,008)		0,051	0,252				-3,419 (p value = 0,00)	3,158 (p value = 0,00)	12,960 (p value = 1,00)
Treatment as expenditure level (T = M)	0,097 (0,043)	-0,045 (0,012)	-0,010 (0,012)	$0,294 \cdot 10^{-4}$ ($0,185 \cdot 10^{-4}$)		0,046	0,185	0,000			-3,145 (p value = 0,00)	2,919 (p value = 0,00)	18,874 (p value = 1,00)
Treatment (T = M) and agricultural employment share	0,097 (0,030)	-0,050 (0,010)	-0,019 (0,013)	$0,370 \cdot 10^{-4}$ ($0,129 \cdot 10^{-4}$)	-0,001 ($0,496 \cdot 10^{-3}$)	0,051	0,277	0,001	-0,024		-3,775 (p value = 0,00)	2,416 (p value = 0,02)	6,565 (p value = 1,00)
Two-steps													
Unconditional convergence	0,082 (0,014)	-0,010 (0,003)				0,010					-3,947 (p value = 0,00)	1,866 (p value = 0,06)	3,314 (p value = 1,00)
Treatment as dummy T=0,1	0,027 (0,013)	-0,043 (0,004)	-0,001 (0,002)	-0,014 (0,004)		0,044	0,014				-3,153 (p value = 0,00)	2,173 (p value = 0,03)	12,393 (p value = 1,00)
Treatment as expenditure level (T = M)	0,029 (0,014)	-0,042 (0,004)	-0,003 (0,002)	$0,966 \cdot 10^{-5}$ ($0,434 \cdot 10^{-5}$)		0,042	0,070	0,000			-3,008 (p value = 0,00)	2,823 (p value = 0,01)	17,607 (p value = 1,00)
Treatment (T = M) and agricultural employment share	0,035 (0,014)	-0,050 (0,005)	-0,010 (0,002)	$0,179 \cdot 10^{-4}$ ($0,069 \cdot 10^{-4}$)	-0,001 ($0,251 \cdot 10^{-3}$)	0,051	0,167	0,000	-0,026		-3,374 (p value = 0,00)	1,916 (p value = 0,06)	6,401 (p value = 1,00)

Table 3: Sample mean elasticities of the conditioning variables (A_0 and s_0) and steady-state growth rate (y^*) with respect to policy treatment (M_s) and agriculture employment share (AG_0) according to different GMM estimates

Estimate		A_0	s_0	y^*
GMM-DIFF (1-step)	M_s		0,174	0,122
	AG_0	-0,205		-0,205
GMM-DIFF (2-steps)	M_s		0,147	0,120
	AG_0	-0,211		-0,211
GMM-SYS (1-step)	M_s		0,563	0,408
	AG_0	-0,150		-0,150
GMM-SYS (2-steps)	M_s		0,517	0,431
	AG_0	-0,187		-0,187

References

- Abraham, F. and Van Rompuy, P. (1995). Regional Convergence in the European Monetary Union. *Papers in Regional Science*, 74(2), 125-142
- Arellano M. (2003). *Panel-data Econometrica. Advanced Texts in Econometrica*, Oxford University Press.
- Arellano M. and Bond S. (1991). Some Tests of Specification for Panel-data: Monte Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies*, n. 58, pp. 277-297.
- Badinger, H., Muller, W.G., Tondl, G. (2002). *Regional convergence in the European Union (1985-1999): a spatial dynamic panel analysis*. HWWA Discussion Paper n.219, Hamburg Institute of International Economics.
- Barro R.J. and Sala-i-Martin X. (1991). Convergence across States and Regions, *Brookings Papers on Economic Activity*, n. 1, pp. 107-182.
- Barro R.J. and Sala-i-Martin X. (1992). Convergence, *Journal of Political Economy*, n. 100, 2 (April), pp. 223-251.
- Barro R.J. and Sala-i-Martin X. (1995). *Economic Growth*. New York: McGraw-Hill.
- Baumol W.J. (1986). Productivity Growth, Convergence and Welfare: What the Long-Run Data Show, *American Economic Review*, n. 76, 5 (December), pp. 1072-1085.
- Bernard, A.B. and Jones, C.I. (1996). Comparing Apples to Oranges: Productivity Convergence and Measurement across Industries and Countries. *American Economic Review*, 86(5), 1216-1238.
- Beugelsdijk M. and Eijffinger S. C. W. (2003). The effectiveness of structural policy in the European Union: an empirical analysis for the EU15 during the period 1995-2001, *CEPR Discussion Paper N. 3879*, London. www.cepr.org.
- Boldrin M. and Canova F. (2001). Europe's Regions. Income disparities and regional policies, *Economic Policy*, April, pp. 207-253.
- Bond, S., Hoeffler, A., Temple, J. (2001). *GMM estimation of empirical growth models*. CEPR Discussion Paper n. 3048, Centre for Economic Policy Research, London.

Bussoletti, S. (2004). *Fondi strutturali e convergenza regionale nella UE allargata. Un approccio con dati panel*. Ph.D. dissertation, Department of Economics, Polytechnic University of Marche, Ancona.

Bussoletti, S. and Esposti, R. (2004). Structural funds, regional convergence and agricultural employment in the enlarged EU. A panel-data approach. Proceedings of the 87th EAAE-Seminar: *Assessing rural development policies of the CAP*, Wien, 21-23 April.

Canova F. and Marcet A. (1995). The Poor Stay Poor: Non-Convergence Across Countries and Regions, *Discussion Paper* n. 1265, CEPR, London.

Carmeci G. and Mauro L. (2003). Imperfect labor market and convergence: theory and evidence for some OECD countries. *Journal of Policy Modeling*, 25 (8), pp. 837-856.

Caselli F., Esquivel G. and Lefort F. (1996). Reopening the Convergence Debate: A New Look at Cross Country Growth Empirics, *Journal of Economic Growth*, 1, pp. 363-389.

Chatterji M. (1993). Convergence Clubs and Endogenous Growth, *Oxford Review of Economic Policy*, Vol. 8, n. 4, pp. 57-69.

Croci Angelini, E. (2002). Quale convergenza? Tendenze evolutive delle disparità di reddito fra le regioni della Unione Europea. In Farina, F., Tamburini, R. (a cura di): *Da Nazioni a Regioni. Mutamenti istituzionali e strutturali dopo l'Unione Monetaria Europea*. Bologna: Il Mulino.

Deller, S.C., Gould, B.W., Jones, B. (2003). Agriculture and rural economic growth. *Journal of Agricultural and Applied Economics*, 35 (3), 517-527.

European Commission (2004). *A new partnership for cohesion. Convergence, Competitiveness, Cooperation. Third report on economic and social cohesion*. Bruxelles: European Commission

Fagerberg J. and Verspagen B. (1996). Heading for Divergence? Regional Growth in Europe Reconsidered. *Journal of Common Market Studies*, Vol. 34 n. 3.

Gaduh, A.B. (2002). *Properties of fixed effects. Dynamic panel-data estimators for a typical growth datasets*. CSIS Working Paper Series, WPE 062, Centre for Strategic and International Studies, Jakarta.

Islam N. (2003). What Have We Learnt from the Convergence Debate?, *Journal of Economic Surveys*, 3, Vol. 17, pp. 309-362.

Judson, R. and Owen, A. (1999). Estimating dynamic panel-data models: a guide for macroeconomists. *Economic Letters*, 65 (1), 9-15.

Lucchetti, R., Papi, L., Zazzaro, A. (2001). Banks' inefficiency and economic growth: a micro-macro approach. *Scottish Journal of Political Economy*, 48 (4), 400-424.

Mankiw N., Romer D. and Weil D.N. (1992). A Contribution to the Empirics of Economic Growth, *Quarterly Journal of Economics*, 107 (2), pp. 407-437.

Molle, W. and Boeckhout, S. (1995). Economic Disparity under Conditions of Integration-A Long Term View of the European Case. *Papers in Regional Science*, 74(2), 105-23.

Neven D. and Gouyette C. (1995). Regional Convergence in the European Community, *Journal of Common Market Studies*, 33 (1), pp. 47-65.

Quah D. (1996). Empirics for economic growth and convergence, *European Economic Review*, 40, pp. 1353-1375.

Sala-i-Martin X. (1996). Regional cohesion: evidences and theories of regional growth and convergence, *European Economic Review*, n. 40.

Sala-i-Martin, X. (1997). I just run two million regressions. *American Economic Review*, 87, 178-183.

Yudong, Y. and Weeks M. (2000). Provincial Income Convergence in China, 1953-1997: A Panel-Data Approach. *Econometric Reviews*, 22(1), pp. 59-77.