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The Impact of Objective 1 Funds on Regional Growth Convergence in the EU

A panel-data approach

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The Impact of Objective 1 Funds on Regional Growth Convergence in the EU

A panel-data approach

Abstract

This article investigates the impact of Objective 1 structural funds expenditure on EU regions by estimating an augmented conditional convergence econometric model. According to this model, growth convergence is influenced by the policy treatment, which affects the regional initial investment rate by interacting with other regional structural variables and eventually influencing its steady state level. The convergence model is specified in a dynamic panel-data form and estimated using a database of 206 EU15 regions observed from 1989 to 2000. A GMM estimation is applied to obtain consistent estimates of both parameter β and impact of the Objective 1 policies.

Keywords: Regional Convergence, Objective 1 Funds, Panel Data, GMM Estimation

J.E.L. Classification: R110, R580, O180

Introduction

This article aims to identify the impact of the European Union (EU) Structural Funds (SF) in Objective 1 regions; that is, those policy measures specifically delivered to regions whose *per capita* (hereafter p.c.) income is less than 75% of the EU average. For this purpose, we assume that structural payments may condition the "natural" convergence process of the poorer European regions towards the richer ones. We estimate, therefore, an augmented conditional regional convergence model to assess whether growth convergence is actually observed over the whole 1989-2000 period, and whether structural payments significantly affect it and differences in this respect emerge across EU regions.

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A data set of more than 200 NUTS II European regions observed over this period enables a dynamic panel-data specification of the conditional convergence model. This dynamic model is estimated by means of an appropriate GMM estimator. Alternative GMM estimates are also proposed and discussed.

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 SF for Objective 1 regions, which means about 0,25% of the whole EU GDP (European Commission, 2004). Nevertheless, the size of the growth gap remains so relevant in absolute terms to motivate serious doubts about the presence of any real convergence process within the Union and about the effectiveness of this financial effort in this respect.

Previous empirical estimates of regional convergence within the EU provide mixed and controversial results. This may be motivated by the large amount of different model specifications, data and econometric methods used in this literature. Croci Angelini (2002) surveyed 16 different estimations of unconditional convergence across the EU published from 1992 to 2000; the convergence rate varies between 0,4% and 2,9%; indeed, however, several studies actually provide evidence against the regional unconditional 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 also when a panel and dynamic specification is used. Canova and Marcet (1995) report a very high convergence speed (about 11% for the EU countries, 23% for the regions). On the contrary, there is an increasing number of recent panel-data studies not showing any clear evidence of unconditional convergence across EU countries and, above all, regions (Boldrin and Canova, 2001). Within this approach, 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

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club-convergence, that is convergence observed within subgroups of regions (Chatterji, 1993; Canova, 1999; Quah, 1996)[1].

Despite this large body of empirical literature, there is far less abundance of empirical analyses about regional convergence conditional on Objective 1 payments (Rodriguez-Pose and Fratesi, 2004; Beugelsdijk and Eijffinger, 2003). In the Third Cohesion Report, the EU Commission (European Commission, 2004) provides an unconditional convergence rate estimate of 0,5% for the 1980-1988 period over the whole EU space; this rate increases to 0,7% and 0,9% in the periods 1989-1993 and 1994-2000, respectively. During these two programming periods, the convergence rate observed only across Objective 1 regions has been much higher, 3,1% and 1,6%, respectively.

This latter evidence, however, is not sufficient to demonstrate a positive impact of SF on this convergence process. In addition, it is of major interest to assess whether this impact actually differs across Objective 1 regions or groups of regions. This difference may occur either for the different amount of funds or for the different selection of interventions to be funded, but also for the different resource endowment across regions in terms of infrastructure, human and knowledge capital, with which the SF themselves interact. Also in this respect, however, sound empirical evidence is lacking or controversial.

This article aims to contribute in this direction.

Conditional β-convergence and policy treatment

State of the art

In the past two decades, a significant and increasing body of empirical studies on regional growth have been based (explicitly or not) on neoclassical convergence theory (Islam, 2003). Actually, the first empirical convergence analysis due to Baumol (1986) was a “simple” a linear regression where the p.c. income growth depended on its initial level as only independent variable (this is the so-called *unconditional convergence* model).

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Subsequent works added some other regressors to this specification. Though these works may be now interpreted as first attempts to estimate *conditional convergence* models, they still used *ad hoc* specifications, that is, not strictly derived from any underlying growth model. In 1992, two seminal empirical works by Barro and Sala-i-Martin (1992) and Mankiw *et al*. (1992), rigorously derived this linear regression specification from the transition dynamics of the neoclassical growth model (in both the Solow-Swan and Cass-Koopmans versions). This is the “formal” or “model-based” specification of the growth convergence model. It still makes the p.c. income growth depend on the initial income level, but other conditioning variables are added, and these are strictly and exclusively justified by the underlying theoretical framework.

One major interest, here, is to assess if policy measures (hereafter “the policy treatment”) affect somehow this regional growth convergence pattern. Most previous empirical assessments of the effect of regional policies on growth seemingly revert to the initial “informal” specification, because difficulties arise when giving these a stronger theoretical justification: that is, when consistently including them as conditioning variables in the formal model.

When formally derived from neoclassical growth theory, the conditional β-convergence[2] model can be written as follows (Mankiw *et al*., 1992; Barro and Sala-i-Martin, 1995):

(1a)

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

On the left-hand side, y_{it} is the i-th region’s p.c. (or per unit of labour) income growth rate over period t, Y_{i0} is the i-th region’s initial (at time 0) p.c. income, X_{i0} denotes a set of other conditioning variables and $T_i=0$ indicates that no policy treatment has been delivered to the i-th region during the period. The right-hand side makes explicit the whole set of conditioning variables: g is the Total Factor Productivity (TFP) growth rate, λ is the speed (or rate) of con-

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vergence, A_{i0} is the i-th region's initial TFP, $0<\alpha<1$ is the coefficient (indicating the capital's share or capital intensity within the economy) of the underlying Cobb-Douglas production function with two factors (K, L) and constant returns to scale, s_{i0} is the i-th region's initial investment rate, n_{i0} is the i-th region's initial population (or employment) growth rate, δ is the capital depreciation rate. According to the underlying growth model, however, g, δ, α and λ are constant parameters across regions and over time. Thus, the remaining conditional variables, beside Y_{i0}, are A_{i0}, s_{i0} and n_{i0}. These are the only legitimate conditioning variables in a neoclassical model-based conditional convergence model. We have different steady-states, therefore conditional convergence, if regions differ in terms of these conditioning variables.

Equation (1a) describes the regional growth convergence pattern toward the respective steady-state. The steady-state output per unit of actual labour, $\hat{Y}_t$, implied by (1a) is (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1995):

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

By substituting equation (2) in equation (1a), we can rewrite the convergence model as follows:

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

In the present study, the main issue is how to include the policy treatment ($T_i \neq 0$), that is Objective 1 expenditure, in the regional conditional convergence model above. In this respect, we may acknowledge that SF influence the regional economy on several aspects and in a complex way (European Commission, 2001 and 2004). Regional macroeconomic models have been proposed to take into account all these possible effects both on the demand and the supply side; some of these approaches are reviewed in Bradley *et al.* (2003). For instance, the neo-Keynesian HERMIN model (Bradley *et al.*, 1995 and 2003) has been adopted to simulate the effect of Objective 1 funds on EU peripheral regions by capturing both the short-run de-

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mand-side and the long-run supply-side impacts, the latter effects incorporating mechanisms that are based on the endogenous growth literature.

Despite the relevance of the demand-side effects, here we want to emphasize how SF influence the long-run supply-side variables, eventually effecting growth convergence. After all, the declared ultimate objective of Objective 1 policies is to permanently reduce the gap between poor and rich EU regions (European Commission, 2001; Rodriguez-Pose and Fratesi, 2004).[3] Limiting the attention only on this aspect does not definitely exhaust the complex issue of SF evaluation, but it still seems consistent with their underlying major policy goal, at least in Objective 1 regions.[4]

According to equation (1a), SF expenditure may influence long-run growth in three different ways, corresponding to the conditioning variables $s_{i0,}$ A_{i0}, g and n_{i0}. First, it may increase the regional investment rate s, thus the capital deepening process eventually leading to higher steady state p.c. capital and GDP. Second, it may increase the regional TFP by either improving its initial level A_{i0} or the growth rate g. Third, it may influence the labour market thus the workforce growth rate n_{i0}, which, in turn, negatively influences the steady state level. In the present paper, however, among these possible effects we only consider the influence of SF on s.

On the one hand, it must beard in mind that making g endogenous or different across regions, as in some endogenous growth models and in the extensive version of the neoclassical model with human capital (Mankiw *et al.*, 1992), would make the concept of growth convergence inherently ambiguous (Islam, 2003). Puigcerver-Peñalver (2004) models the impact of Objective policy following this approach, but it must be acknowledged that under this hypothesis the neoclassical growth convergence model does not seem the appropriate theoretical framework. Linking SF expenditure to the regional initial TFP can be more correct and could be also related to regional structural characteristics, in particular sectoral composition. This approach has been recently followed by De la Fuente (1996) and Esposti (2006).

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On the other hand, Objective 1 funds may favour unemployment reduction but this effect can not be simply expressed in terms of n_{i0}. In the neoclassical growth model, n_{i0} indicates the regional initial population (or employment) growth rate under the implicit assumption of full employment or of a constant employment rate over time and across regions. However, the employment rate largely differs across the EU15 regions and also evolved differently during the 1990s (Paci *et al*., 2002). Thus, GDP growth per labour unit rather than p.c. GDP growth should be used as dependent variable in equation (1a) to take account of unemployment reduction induced by SF. It follows that n_{i0} should express employment growth rather than population growth, but still indicating long-term changes across regions and over time, as a consequence of structural behavioural changes, particularly participation to labour market, fertility and migration rates. These behavioural can be hardly be affected by some regional policy. In fact, to our knowledge, no empirical study has modelled the impact of SF on regional growth convergence in terms of employment growth.

In fact, Objective 1 funds should be prevalently considered as investments, as most of them (92% in the whole 1989-1999 period, 98% in the 1994-1999 programming period) concentrate on three main areas: infrastructure, human capital, support to other (mainly private) investments, R&D included (Bussoletti, 2004; European Commission, 2001 and 2004; Rodriguez-Pose and Fratesi, 2004).[5]

The model

We may conclude that the most natural way to include SF into a regional growth convergence model is to make them affect the investment rate, s, given that they are mostly investments. According to this straightforward argument, these funds are here interpreted as an increase of the capital stock in the unit of time, that is $\dot{K} = \partial K / \partial t$, and, consequently, of the investment rate $s = \dot{K} / \psi$, where ψ is the regional GDP. Considering SF expenditure as capital accumulation has the advantage to model the different impact of the aforementioned different areas of intervention (infrastructure, human capital and R&D), and how they interact in shaping the growth convergence process.

Distinguishing among different kinds of investment (human capital, infrastructure, R&D and so on) in analysing Objective 1 SF is not new and is also consistent with the different strategic axes designed for this policy (European Commission, 2001). In some studies, the policy treatment itself is explicitly distinguished among these different investment categories, but this is done only at the country level or considering single regional cases (Bradley *et al.*, 2003; Rodriguez-Pose and Fratesi, 2004). Unfortunately, in fact, current available data do not allow to attribute the whole Objective 1 expenditure to different investments at the regional level, unless we make this attribution exclusively on the basis of the underlying financing structural fund, that is ERDF, ESF, etc. (Puigcelver-Peñalver, 2004). However, it is often neither possible nor appropriate to associate the expenditure of a given EU structural fund to a specific investment typology.

One possible way to proceed, therefore, is to model at the regional level the interaction between the overall amount of policy expenditure and the different capital assets (infrastructure, human capital, R&D), or some proxies of them. In fact, we can interpret the interaction parameters as combination of two effects. On the one hand, this interaction depends on the underlying unobserved share of SF expenditure invested in that specific asset. On the other hand, it summarizes all those specific economic and technical characters affecting each capital asset's formation; in particular, increasing or decreasing returns associated to each investment, depending on its depreciation and obsolescence, congestion or spillover effects and other relevant aspects in this respect. [6]

Here, we model these aspects by specifying a *capital formation function*. Firstly, we can cumulate past expenditure in new capital formation by measuring the treatment as a weighted

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sum of past policy expenditure per labour unit within the region, that is $T_{it} = \sum_{s=0}^{Z} w_s M_{it-s}$,

where w_s is the weight indicating the "portion" of the policy expenditure per labour unit, M, delivered at time t-s affecting the outcome at time t, and Z is the maximum lag. Secondly, we can derive the following relation between the regional investment rate s and this policy treatment, representing how this public expenditure converts into the abovementioned different capital assets and interacts with them (see the appendix for the specification of the capital formation function and detailed derivation of equation (3)):

$$\begin{aligned}(3)\quad \ln s_{i0} &= \gamma_i + \phi_0 \ln T_{i0} + \phi_1 \ln H_{i0} + \phi_2 \ln RDpr_{i0} + \phi_3 \ln RDpu_{i0} + \phi_4 \ln I_{i0} \\ &+ \tau_1 \ln T_i \ln H_{i0} + \tau_2 \ln T_i \ln RDpr_{i0} + \tau_3 \ln T_i \ln RDpu_{i0} + \tau_4 \ln T_i \ln I_{i0} - \ln Y_{i0}\end{aligned}$$

where: H_{i0} = initial human capital in the i-th region, i.e. the proportion of regional population enrolled at the University degree level on total population; $RDpr_{i0}$ = initial regional private (or business) R&D expenditure per labour unit; $RDpu_{i0}$ = initial regional public (government) R&D expenditure per labour unit; I_{i0} = initial regional index of transport infrastructure endowment.

According to this representation, in particular, the structural policy affects growth convergence by favouring the capital deepening process in Objective 1 regions, and this policy impact is generated interacting with the current level of regional capital endowment in terms of human capital, R&D, infrastructure.

Substituting equation (3) in (1a) and adopting a panel-data specification with a region-specific constant term a_i, we obtain a regional convergence model conditional on the policy treatment T_{i0}:

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(4)

$$E\left(y_{it} \middle| Y_{i0},\ T_{i0} = \sum_{s=-Z}^{0} w_s\, M_{is},\ H_{i0},\ RDpr_{i0}, RDpu_{i0}, I_{i0}, n_{i0} \right) = a_i + \varphi_0 \ln T_{i0} + \varphi_1 \ln H_{i0} + \varphi_2 \ln RDpr_{i0} + \varphi_3 \ln RDpu_{i0}$$
$$+ \varphi_4 \ln I_{i0} + \varphi_5 \ln T_{i0} \ln H_{i0} + \varphi_6 \ln T_{i0} \ln RDpr_{i0} + \varphi_7 \ln T_{i0} \ln RDpu_{i0} + \varphi_8 \ln T_{i0} \ln I_{i0} + \beta^* \ln Y_{i0} + \chi \ln\left(n_{i0} + g + \delta\right)$$

where:

$$a_i = t\, g + \left(1 - e^{-\lambda t}\right) \ln A_{i0} + \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \gamma_i$$

$$\varphi_0 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \phi_0 \ , \quad \varphi_1 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \phi_1 \ , \quad \varphi_2 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \phi_2 \ , \quad \varphi_3 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \phi_3 \ ,$$

$$\varphi_4 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \phi_4 \ , \quad \varphi_5 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \tau_1 \ , \quad \varphi_6 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \tau_2 \ , \quad \varphi_7 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \tau_3 \ ,$$

$$\varphi_8 = \left(1 - e^{-\lambda t}\right) \frac{\alpha}{1-\alpha} \tau_4$$

$$\beta^* = \frac{\beta}{1-\alpha} = -\frac{\left(1 - e^{-\lambda t}\right)}{1-\alpha}$$

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

Equation (4) is an *augmented conditional growth convergence model*, where the conventional conditioning variables ($\ln A_{i0}$ and n_{i0}) are now combined with new ones (T_{i0}, H_{i0}, $RDpr_{i0}$, $RDpr_{i0}$, I_{i0}). These variables are now part of the formal conditional convergence model affecting the investment rate, s, and, in turn, the steady state level.

Equation (4) is still a "reduced" from model, because the underlying structural parameters $\alpha, \lambda, \phi_0, \phi_1, \phi_2, \phi_3, \phi_4, \tau_1, \tau_2, \tau_3$ and τ_4 can not be directly estimated. Nonetheless, by combining equations (1a), (3) and (4), they can be indirectly obtained through the estimated reduced-form parameters as follows:

$$\alpha = \frac{\chi}{\beta^*}$$

$$\lambda = -\frac{\ln\left[\beta^* - \chi + 1\right]}{t}$$

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$$\phi_0 = -\frac{\varphi_0}{\chi}, \phi_1 = -\frac{\varphi_1}{\chi}, \phi_2 = -\frac{\varphi_2}{\chi}, \phi_3 = -\frac{\varphi_3}{\chi}, \phi_4 = -\frac{\varphi_4}{\chi}, \tau_1 = -\frac{\varphi_5}{\chi}, \tau_2 = -\frac{\varphi_6}{\chi}, \tau_3 = -\frac{\varphi_7}{\chi}, \tau_4 = -\frac{\varphi_8}{\chi}$$

According to this convergence model, any region follows its own steady state growth path, as indicated by the estimated reduced-form parameters. In particular, β makes it possible to assess whether convergence occurs and to derive its speed (λ); parameters χ and φ's indicate whether or not convergence is conditional, and φ's also reveal if the policy treatment has an effect and which is its magnitude. In addition, other individual effects ($\ln A_{i0}$ and γ_i), affecting the regional initial investment rate and productivity and, consequently, the region-specific steady state level, are now included in the region specific a_i term, which thus represents a further conditioning variable.[7]

According to equation (4), in any region, either treated or not, the growth convergence process is conditioned on its initial level of *H*, *I*, *RDpr* and *RDpu*. The difference between treated and not treated regions, however, is that in the former case the policy treatment *T* itself behaves as a conditioning variable, as well as its interaction with *H*, *I*, *RDpr* and *RDpu*. In the latter case, the treatment is "off", that is *T*=0, and, consequently, also all the interaction terms are 0.[8]

It is also possible to express the impact of additional SF payments on treated regions in terms of elasticity; from equation (3) it follows:

(5a) $$\varepsilon^i_{s,M} = \frac{\partial \ln s_{i0}}{\partial \ln M_{is}} = \phi_0 + \tau_1 \ln H_{i0} + \tau_2 \ln RDpr_{i0} + \tau_3 \ln RDpu_{i0} + \tau_4 \ln I_{i0}$$

which also leads to the elasticity expressing how, through s_{i0}, they actually affect the steady-state output per unit of actual labour (2)[9]:

(5b) $$\varepsilon^i_{\hat{Y},M} = \frac{\partial \ln \hat{Y}}{\partial \ln M_{is}} = \frac{\alpha}{1-\alpha}\left(\phi_0 + \tau_1 \ln H_{i0} + \tau_2 \ln RDpr_{i0} + \tau_3 \ln RDpu_{i0} + \tau_4 \ln I_{i0}\right)$$

Despite the fact that parameters of equations (5a) and (5b) are constant across regions, they may still eventually generate different elasticities when multiplied by the region-specific

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terms, *H*, *I*, *RDpu* and *RDpr*. Therefore, the impact of SF may differ both in magnitude and in sign across treated regions, and this is achieved without the introduction of region-specific slope coefficients. In this respect, the model allows to evaluate the SF impact over the whole Objective 1 EU space, but also the different behaviour of single Objective 1 regions or group regions (for instance, Objective 1 regions of a given EU country).

Data description

Comparable GDP, population and other economic data at the NUTS II regional level are taken from the Newcronos Regio database (Eurostat); GDP data are expressed in Purchasing Power Standard (PPS) currency.[10] This regional database covers all the 206 EU15 NUTS II regions over the whole 1989-2000 period.[11] In order to be fully consistent with the neoclassical growth model, we use the GDP growth per labour unit as dependent variable of equation (4). P.c. GDP growth is more frequently used in empirical work, but it implicitly assumes full employment or a constant employment rate over time and across regions, eventually making the two growth rates equivalent. As mentioned, however, employment rates and their evolution over time largely differ across the EU15 regions. Use of p.c. GDP growth might therefore generate a significant bias in parameter estimates.

Currently available EU regional data provide comparable regional employment growth rate, that is, 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 $(\delta + g) = 0{,}05$, which is what is done here.[12]

Data about SF expenditure in Objective 1 regions refer to annual payments in the two programming periods 1989-1993 and 1994-1999. In order to include the total contribution, all SF are considered (ERDF, which is the main contributor to Objective 1 programme, ESF, EAGGF and FIFG). Unfortunately, a single centralised database on SF expenditure at regional level does not exist. This variable has therefore been reconstructed on the basis of in-

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formation provided by the European Commission Annual Reports on SF payments and considering both regional and multiregional programmes.[13]

All Objective 1 payments are expressed in PPS currency, using the same conversion index as employed by EUROSTAT to convert regional income into the common comparable currency. Table 1 reports in detail the average Objective 1 per capita payments during the period under study, distinguished between regional and multiregional funds.

With respect to the other conditioning variables, *H*, *I*, *RDpr* and *RDpu*, it must be reminded that they indicate the respective capital endowment per unit of labour (see the appendix for details). These variables can be hardly measured with precision, given the currently available information. Nonetheless, we can use proxies for them to have a reliable representation of the different endowment across regions.

For *H*, we use as proxy the share of tertiary level students on total population; this seems more robust than the share of tertiary level graduates on total population, which shows a much larger difference across countries due to different age structure and education systems. Data are taken from Newcronos Regio database (Eurostat) and cover the period 1993-1998. Thus, the values of *H* before 1993 and after 1998 are assumed to be equal to the 1993 and 1998 levels, respectively.

For *RDpu* and *RDpr*, we use the respective data reported in the Newcronos Regio database (Eurostat) and divided by the units of labour. To be consistent with the other variables, this R&D expenditure has been converted in the PPS currency.

Finally, *I* has been proxied by a synthetic variable indicating the regional infrastructure endowment per inhabitant. This variable have been obtained starting from two index variables calculated at the NUTS 3-region level by the European Spatial Planning Observation Network (ESPON, 2004) indicating the "Potential accessibility multimodal" and the "Connectivity to transport terminals by car (hours) of the capital or centroid representative of the NUTS3". These two variables have been firstly indexed with respect to the respective maximum values

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and then cumulated to have an aggregate index varying between 0 and 2. Finally, for any NUTS 2 region this index has been computed as weighted average of the respective NUTS 3 regions.[14]

For all model variables, table 2 reports the average values in Objective 1 regions by country. With respect to the growth variable, it can be noticed that Portuguese, German and French Objective 1 regions show the lowest GDP per labour unit. German and French cases, however, concern quite specific and peculiar situations, i.e. the former Eastern Germany and Overseas regions, respectively. Among these poorest cases, German regions show the best growth performance whereas, on the contrary, French and Portuguese ones achieve a slower growth, a performance similar to Spanish regions, which have, however, the highest initial GDP levels on average.

In terms of conditioning variables, large disparities can be observed among national groups of Objective 1 regions. The highest average value of SF expenditure (*M*) is observed in the Greek and Portuguese regions, while the lowest levels concern French and German regions, despite their larger growth lag. This confirms that these latter cases are somehow anomalous with respect to the rest of the Objective 1 EU space. In fact, in terms of R&D investment, German regions show by large the highest value, as well as the French cases, where the very low private expenditure is compensated by high public R&D. Less divergence can be observed with respect to *H* and *I*, though German regions excel, again, in terms infrastructure endowment and Greek ones in terms of education levels.[15]

[Tables 1 and 2 here]

The estimated model

The regional conditional convergence model in equation (4) is estimated using the regional panel database described above.[16] The dynamic panel-data specification has become frequent

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in growth convergence empirical studies (Carmeci and Mauro, 2003; Caselli *et al.*, 1996; Yudong and Weeks, 2000). The simplest dynamic version is an AR(1) model:

(6)

$$y_{it} = a + \rho\, y_{it-1} + \varphi_0 \ln T_{it-1} + \varphi_1 \ln H_{it-1} + \varphi_2 \ln RDpr_{it-1} + \varphi_3 \ln RDpu_{it-1} + \varphi_4 \ln I_{it-1} + \varphi_5 \ln T_{it-1} \ln H_{it-1}$$
$$+ \varphi_6 \ln T_{it-1} \ln RDpr_{it-1} + \varphi_7 \ln T_{it-1} \ln RDpu_{it-1} + \varphi_8 \ln T_{it-1} \ln I_{it-1} + \beta^* \ln Y_{it-1} + \chi \ln\left(n_{it-1} + g + \delta\right) + \varepsilon_{it}$$

where ρ is the first-order autocorrelation coefficient. T_{it-1} indicates the regional policy treatment here specified as $T_{it-1} = \sum_{s=-1}^{-3} \frac{1}{3} M_{it-s}$, that is a three years average expenditure per labour unit (M_{it}), to mitigate the relevant variation usually observed on a yearly basis.

The error term of equation (6) contains the region-specific effect as follows:

(7a) $\varepsilon_{it} = \mu_i + \nu_{it}$

It therefore comprises a time-constant and a time-varying component, but with both varying over the *cross section* dimension. If the individual effect is assumed fixed (non-random), it follows:

(7b) $\varepsilon_{it} = \mu_i + \nu_{it} \Rightarrow \sigma(\varepsilon_{it}) = \sigma_\nu$

and the constant term now becomes $a_i = (a + \mu_i)$, i.e. region-specific as in equation (4). Alternatively, a random region-specific effect may be assumed, with $E(\mu_i) = 0$ and $\sigma(\mu_i) = \sigma_i$. From this it follows that:

(7c) $\varepsilon_{it} = \mu_i + \nu_{it} \Rightarrow E(\varepsilon_{it}) = E(\mu_i) + E(\nu_{it}) = 0_i$; $\sigma(\varepsilon_{it}) = \sigma_\nu + \sigma_i + E(\mu_i\, \nu_{it})$

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

Islam (2003) and Abreu *et al.* (2005) underline that the random effect specification is not acceptable under the neoclassical growth framework, because it implies that individual effects are correlated with some regressors (expected to be exogenous), As evident from equation (4),

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both contains the same parameters related to the underlying regional growth pattern. Random effects would thus generate biased estimates because of endogeneity bias. For this major reason, we only consider here the fixed effect version of equation (6).

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. Introducing the lagged values of the dependent variable, however, implies that the i.i.d. hypothesis of the v_{it} term no longer holds true, because it is correlated with the lagged dependent variable. In other words, y_{it-1} is endogenous (Arellano, 2003).

Consequently, an instrumental variable estimator must be used to achieve consistent estimates of parameters in equation (6). Here, the GMM estimator proposed by Arellano and Bond (1991) is adopted. This requires rewriting equation (6) in the first-differences (GMM-DIFF estimator), because this generates a first differenced error term $\Delta\varepsilon_{it}$ that is uncorrelated with any lagged level variable y_{it-s} ($\forall s \geq 2$). These lagged variables are thus valid instruments according to the moment (orthogonality) condition $E[\Delta\varepsilon_{it}\ y_{it-s}]=0$. The one-step and two-step GMM estimators proposed by Arellano and Bond (1991) are applied. Although both are consistent, the latter provides asymptotically efficient estimates.[17]

Blundell and Bond (1998) showed that the GMM-DIFF estimator may give rise to marked 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. These authors suggest an alternative GMM estimator (GMM-SYS), where a system of equations is estimated by adding equations in levels to first-difference equations, given that, 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 GMM-SYS estimator is also adopted here.

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The improvement provided by the GMM-SYS estimator in finite samples, however, is questioned in several empirical applications where GMM-DIFF estimates appear to be more robust especially when the two-step procedure is followed (Lucchetti *et al*., 2001). In general terms, it is often concluded that no single estimator of dynamic panel models is superior in all circumstances (Badinger *et al*., 2002). Nevertheless, in the recent growth convergence literature, the GMM-SYS estimator provided more moderate and realistic rates of convergence, ranging from 2 to 4% per annum, quite close to most cross-section studies.[18]

A major issue concerning GMM estimators is the selection of the instrumental variables. Here, all available and admitted lagged income growth variables are considered. We also include as instruments the out-sample observations, that is the annual growth rates of GDP per labour unit observed in the period 1980-1988. To assess the consistency of the instruments selection, an overidentifying restrictions (Sargan) test is adopted (Arellano, 2003).[19] 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 arise from the incorrect specification of the dynamic structure of the model. Adopted here are the first and second order serial correlation LM tests proposed by Arellano and Bond (1991).[20] If the AR(1) specification holds true, we should observe first order correlation (generated by first-differentiation) but no second order correlation.

Results

Tables 3 and 4 report the four GMM estimates (one-step and two-step GMM-DIFF and GMM-SYS) of the dynamic model (equation (6)). Results are firstly presented under the unconditional convergence case (table 3); conditioning variables are then added (table 4).

Under the unconditional convergence model, in all four estimates the autocorrelation coefficient is quite low (always less than 0,1 in absolute value), but statistically different from 0 and

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negative in the case of GMM two-step estimate. In the conditional convergence model, however, the autocorrelation coefficient is always positive, though still quite little and statistically different from 0 only in the two-step GMM-DIFF case. This positive value suggests slight persistency in growth rates and implies a downward correction of the β coefficient estimate. In any case, such a low autocorrelation coefficient tends to exclude any problem of non-stationarity and may reduce the gain obtained with the GMM-SYS estimation.

β convergence is observed across all specifications and estimators both in the unconditional and conditional convergence case. Confirming previous evidence, however, the GMM-DIFF estimation of the conditional convergence rate λ is higher than the GMM-SYS one (4,2% and 1,9%, respectively, in the two step case), though the difference is less remarkable than observed in other studies (Bond *et al.*, 2001).

Major interest in estimation results concerns the role of the conditioning variables (table 4). As expected, two-step GMM estimates provide more statistically significant estimates; in addition, the GMM-DIFF estimates seem to perform better in this respect. In particular, with the two-step GMM-DIFF estimation all estimated parameters are statistically different from zero and behave correctly, according to expected signs.

More in detail, the parameter concerning employment growth (χ) is always negative, as expected, and mostly statistically significant. The significant downward impact on the regional growth rate ranges between 0,045 and 0,105. These values play a role in calculation of the implicit structural parameters, given that χ affects α, ϕ*'s* and τ*'s* and the respective elasticities.

In addition, all GMM estimates provide similar evidence about the role of *H*, *RDpr*, *RDpu* and *I*, as indicated by the estimated φ_1, φ_2 φ_3 and φ_4. As might be expected, the impact of *H*, *RDpr* and *I* on regional growth performance, given the initial GDP per unit of labour, is positive and always statistically significant under the two-step GMM-DIFF case, with *H* showing the larg-

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est impact and *I* the smallest one. The only negative value concerns *RDpu*. This result, observed in all GMM estimates, should not be interpreted as a negative effect of this variable on regional growth by itself, but as a substitution relationship between *RDpu* and *RDpr,* that makes the latter overwhelm, and eventually disguise, the effect of the former.

Despite these quite homogenous and robust results, the impact of Objective 1 SF is not so immediate. On the one hand, the estimated φ_0 is always negative, though statistically different from 0 only in the two-step GMM-DIFF case. On the other hand, however, the impact of variable *T* (the policy treatment) on the regional growth performance does not only depend on this parameter, because it is also affected by its interaction terms with *H*, *RDpr*, *RDpu* and *I*. As mentioned, the combination of these interaction terms can generate a different outcome across regions, both in sign and magnitude, of Objective 1 expenditure.

[Tables 3 and 4 here]

The elasticities reported in table 7 thus clarify the impact of the policy treatment over the whole set of Objective 1 regions and by country regional groups. Considering all Objective 1 regions, it emerges an impact whose size significantly varies across different GMM estimates. Nonetheless, it is always positive, thus indicating that the conditioning effect of the policy treatment on regional growth convergence goes in the expected direction. Moreover, the elasticity is quite limited in magnitude, in particular considering the two-step GMM-DIFF case that shows, as mentioned, the best statistical performance and robustness. Nonetheless, it largely varies between 0,04 and 0,14 with respect to the investment rate, and between 0,05 and 0,51 with respect to the steady state output per unit of labour.

When computed region-by-region or by clusters of regions, however, it emerges that these elasticities may differ even more largely. Thus, the impact of Objective 1 funds may indeed be negligible or even negative in several regional cases or groups. The highest positive impact

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of SF is observed in French Objective 1 regions, where the elasticity with respect to $\hat{Y}$ ranges between 0,35 and 1,18. On the contrary, Germany, Greece and Spain show very low elasticity and even negative values under the two-step GMM-DIFF case. If we limit our attention to this latter estimate, we can observe that elasticity with respect to $\hat{Y}$ is greater than 0,15 only for France (0,40) and Portugal (0,17), almost negligible in Italy (0,02) and in the Other Objective 1 regions (0,07), negative in Germany, Greece and Spain (-0,04, -0,03 and -0,02, respectively).

A limited but positive impact of Objective 1 funds over the whole EU space, with a negligible, or even negative, effect in some specific cases is, thus, the main evidence emerging from model estimates. In general terms, this result confirms some previous studies on the subject using a similar model specification and estimation approach (Rodriguez-Pose and Fratesi, 2004; Beugelsdijk and Eijffinger, 2003). In particular, Beugelsdijk and Eijffinger (2003) obtained similar results with regard to 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 policy treatment in terms of payment growth rate instead of payment level, the former apparently being much less regular and potentially more statistically "noisy" over a short time period.

It is of major interest here to assess the consistency of GMM estimates with the underlying theoretical framework. Besides the statistical significance and correct sign of most of the parameters, the key evidence in this respect is provided by the implicit structural parameters (table 5). In particular, the α parameter indicates the capital intensity (that is, the capital income 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 unreliable or even impossible. α must range between 0 and 1 and should realistically fall in the 0,30-0,50 interval. The GMM-DIFF estimation generates values of α close to this interval; it varies between 0,49

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of the one-step case and 0,54 of the two-step estimation. On the contrary, the GMM-SYS provides less reliable values ranging from 0,78 to 0,82.

Comparing the GMM estimates, one major conclusion is that there is no evidence that significant gain can be obtained by passing from the GMM-DIFF to the GMM-SYS estimation. On the contrary, both in terms of statistical significance and of theoretical consistency, the GMM-DIFF estimation seems to outperform the GMM-SYS. This is not surprising, however, because the GMM-SYS can improve the estimation performance, particularly under the already-mentioned specific conditions concerning the sample and the model, but these conditions do not hold true in the present case.

The choice of the appropriate instruments set, in fact, may be even more critical in the GMM-SYS approach. Table 6 reports the diagnostic statistical tests in this respect. Firstly, LM tests support the AR(1) specification. As expected, always rejected is the hypothesis of no first-order serial correlation of the differentiated error terms, while the hypothesis of no second-order correlation is accepted. This dynamic specification also drives the choice of the instruments. In this respect, however, the Sargan tests confirm that the instrumental variables have been selected correctly both in the GMM-DIFF and GMM-SYS, since the hypothesis that they are orthogonal to the differentiated residuals can be accepted.

The validity of the extra-instruments included in 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. According to this statistic, the validity of the extra-instruments may be accepted.

[Tables 5, 6 and 7 here]

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Some final remarks

This article attempted to estimate the impact of EU SF on Objective 1 regions within a growth convergence model. By adopting a panel-data specification, the estimated conditional convergence model is derived from the underlying neoclassical growth model where SF expenditure is included as determinant of the regional investment rate.

The results confirm that dynamic specification may be more appropriate in this empirical application. In general terms, and regardless of the estimator adopted, growth convergence is observed. As demonstrated in the recent literature on the topic, the convergence rate may significantly vary across alternative specifications and estimators. Here, however, this variability seems less evident, as estimates of the conditional convergence rate have ranged between 1,9% and 4,9%, not so different from what usually obtained in cross-sectional studies (2-3%).

With regard to conditioning variables, a positive impact of SF on Objective 1 regions is confirmed over the whole EU space, although its statistical significance and magnitude may vary across alternative estimators. The impact of the Objective 1 policy on growth, however, is generally quite limited and may become negligible and even negative is some regional cases. For instance, when regions are grouped by country, a negative effect may observed for German, Greek and Spanish Objective 1 regions. On the contrary, the French Objective 1 regions show the highest policy treatment effect.

Comparing these results with previous studies on the impact of Objective 1 funds also emphasizes how relevant some apparently marginal issues may be. First of all, the lagged effect of funds over time is of major relevance and it is often disregarded in empirical works on the topic. In more general and, perhaps, obvious terms, the quality of the conditional convergence model estimates critically depends on how the policy under study is included in the model itself and how the respective data are treated.

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APPENDIX

Derivation of equation (3)

By definition of investment rate, the following identity holds:

$$s_{i0} = \frac{\dot{K}_{i0}}{\Psi_{i0}} = \frac{\dot{K}_{i0}/L_{i0}}{\Psi_{i0}/L_{i0}} = \frac{\dot{k}_{i0}}{Y_{i0}}$$

where Ψ_{i0} and K_{i0} are the initial regional GDP and capital, respectively; Y_{i0} and k_{i0} are the initial GDP and capital per unit of labour, respectively, and $\dot{k}_{i0} = \frac{\partial k_{i0}}{\partial t}$. Taking the logarithms, we can write:

(A.1) $\ln s_{i0} = \ln \dot{k}_{i0} - \ln Y_{i0}$

We assume that in the Cobb-Douglas production function underlying the neoclassical growth model, we can decompose the aggregate capital K in different assets, as done in previous studies for instance to distinguish physical capital and human capital (Mankiw *et al.*, 1992). Here, we decompose K in: private physical capital (Γ), human capital (Λ), public physical capital or infrastructure (Θ), private knowledge capital or private R&D (Πpr), public knowledge capital or public R&D (Πpu). We can thus re-write the Cobb-Douglas production function as follows:

(A.2) $\psi_{i0} = A_{i0} K_{i0}^{\alpha} L_{i0}^{(1-\alpha)} = A_{i0} \left[\Lambda_{i0}^{b} \Theta_{i0}^{c} \Pi pr_{i0}^{d} \Pi pu_{i0}^{h} \Gamma_{i0}^{(1-b-c-d-h)} \right]^{\alpha} L_{i0}^{(1-\alpha)}$

where *b*, *c*, *d* and *h* are fixed parameters, and constant returns to scale are assumed both for the production function and the aggregation of capital.

In terms of capital per unit of labour we can write:

(A.3) $\frac{K_{i0}}{L_{i0}} = k_{i0} = \frac{\Lambda_{i0}^{b}}{L_{i0}^{b}} \frac{\Theta_{i0}^{c}}{L_{i0}^{c}} \frac{\Pi pr_{i0}^{d}}{L_{i0}^{d}} \frac{\Pi pu_{i0}^{h}}{L_{i0}^{h}} \frac{\Gamma_{i0}^{(1-b-c-d-h)}}{L_{i0}^{(1-b-c-d-h)}} = H_{i0}^{c} I_{i0}^{c} RDpr_{i0}^{d} RDpu_{i0}^{h} P_{i0}^{(1-b-c-d-h)}$

where *H*, *I*, *RDpr*, *RDpu*, *P* indicate the endowment per unit of labour of human capital, infra-structure, private R&D, public R&D and private physical capital, respectively.

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If we consider an investment (a SF payment) per unit of labour T_i with an unknown distribution among different assets, we can assume the following generic *new capital formation function*:

(A.4) $\dot{k}_{i0} = f\left(T_{i0}, k_{i0}\right)$

that is, the growth of capital per labour unit in the i-th region depends on the initial capital stock and on the policy expenditure T_{i0}. The latter is expected to have a positive effect on $\dot{k}$, though this effect may differ according to the above-mentioned investment typologies (Γ, Λ, Θ, Πpr, Πpu).

The impact of a given investment in terms of new capital formation, however, also depends on the initial stock of capital. New investments, in fact, may show either increasing or decreasing returns with respect to capital formation due to several specific aspects, such as depreciation, obsolescence, spillover or congestion effects, etc. Therefore, k_{i0} may influence the effect of an investment T_{i0} on $\dot{k}_{i0}$ in different ways and this is strongly related to the investment typology.

We can approximate this generic capital formation function with a flexible functional form, like the translog:

(A.5) $\ln \dot{k}_{i0} = a_0 + a_1 \ln T_{i0} + a_2 \ln k_{i0} + a_3 \ln T_{i0} \ln k_{i0}$

By substituting equation (A.3) in (A.5) we obtain:

(A.6)

$$\ln \dot{k}_{i0} = a_0 + a_1 \ln T_{i0} + a_2 b \ln H_{i0} + a_2 c \ln I_{i0} + a_2 d \ln RDpr_{i0} + a_2 h \ln RDpu_{i0} + a_2\left(1-b-c-d-h\right)\ln P_{i0}$$
$$+ a_3 b \ln T_{i0} \ln H_{i0} + a_3 c \ln T_{i0} \ln I_{i0} + a_3 d \ln T_{i0} \ln RDpr_{i0} + a_3 h \ln T_{i0} \ln RDpu_{i0}$$

Unfortunately, neither a reliable measurement nor a proxy of P_{i0} at the regional level can be easily identified. Moreover, our attention is mainly on the above-mentioned prevalent kinds of investment supported by Objective 1 funds. Therefore, in equation (A.6) we as-

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sume no interaction between the policy treatment T_{i0} and P_{i0} and we treat P_{i0} as an unobserved individual (regional) parameter: $\ln P_{i0} = \xi_i$.

It follows:

$$\text{(A.7)} \quad \begin{aligned} \ln \dot{k}_{i0} &= \gamma_i + \phi_0 \ln T_{i0} + \phi_1 \ln H_{i0} + \phi_2 \ln RDpr_{i0} + \phi_3 \ln RDpu_{i0} + \phi_4 \ln I_{i0} \\ &+ \tau_1 \ln T_{i0} \ln H_{i0} + \tau_2 \ln T_{i0} \ln RDpr_{i0} + \tau_3 \ln T_{i0} \ln RDpu_{i0} + \tau_4 \ln T_{i0} \ln I_{i0} \end{aligned}$$

Where:

$\gamma_i = a_0 + a_2(1-b-c-d-h)\xi_i$, $\phi_0 = a_1$, $\phi_1 = a_2 b$, $\phi_2 = a_2 d$, $\phi_3 = a_2 h$, $\phi_4 = a_2 c$, $\tau_1 = a_3 b$, $\tau_2 = a_3 d$, $\tau_3 = a_3 h$, $\tau_4 = a_3 c$.

Substituting equation (A.7) in (A.1), we obtain equation (3):

$$\text{(3)} \quad \begin{aligned} \ln s_{i0} &= \gamma_i + \phi_0 \ln T_{i0} + \phi_1 \ln H_{i0} + \phi_2 \ln RDpr_{i0} + \phi_3 \ln RDpu_{i0} + \phi_4 \ln I_{i0} \\ &+ \tau_1 \ln T_{i0} \ln H_{i0} + \tau_2 \ln T_{i0} \ln RDpr_{i0} + \tau_3 \ln T_{i0} \ln RDpu_{i0} + \tau_4 \ln T_{i0} \ln I_{i0} - \ln Y_{i0} \end{aligned}$$

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Table 1: Statistical dispersion of *per capita* SF payments (in PPS) in Objective 1 regions, 1989-1999 - CV expressed in %

Year	No. of regions	Average: Regional Funds	Average: Multiregional Funds	Average: Total Funds	Standard Deviation: Regional Funds	Standard Deviation: Multiregional Funds	Standard Deviation: Total Funds	Coefficient of Variation (CV): Regional Funds	Coefficient of Variation (CV): Multiregional Funds	Coefficient of Variation (CV): Total Funds
1989	45	81,9	67,0	148,9	65,6	69,9	85,9	80,1	104,3	57,7
1990	45	98,6	89,4	188,0	132,0	173,2	203,8	133,9	193,7	108,4
1991	51	85,6	64,2	149,8	75,0	78,4	97,7	87,6	122,1	65,2
1992	51	147,7	73,7	221,4	174,4	108,7	198,0	118,1	147,5	89,4
1992	51	132,2	99,5	231,7	103,2	106,3	135,9	78,1	106,8	58,7
1994	58	130,9	211,6	342,5	143,1	664,4	790,7	109,3	314,0	230,9
1995	58	132,4	155,0	287,4	106,5	213,7	302,9	80,4	137,9	105,4
1996	58	127,2	228,8	356,0	158,6	641,1	785,4	124,7	280,2	220,6
1997	57	146,9	197,5	344,4	143,4	429,3	559,1	97,6	217,4	162,3
1998	57	157,5	285,7	443,2	153,5	649,0	777,0	97,5	227,2	175,3
1999	57	159,6	177,2	336,8	123,1	249,1	321,8	77,1	140,6	95,5

Source: Our elaboration on European Commission

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Table 2: Average values (at 1994 where not indicated otherwise) of the model variables in Objective 1 regions (according to the 1994-1999 programming period)

	N. of regions	avg. growth rate of GDP per labour unit, 2000-1989 (%)	GDP per labour unit (PPS)	*M* (PPS)	*H*	*RDpr* (PPS)	*RDpu* (PPS)	*I***
All EU15 Obj. 1 regions	57	4,5%	28535	866,0	2,36	67,1	91,7	0,44
France - Obj. 1 regions	6	3,7%	19764	229,2	2,01	12,4	210,7	0,36
Germany - Obj. 1 regions	6	6,9%	24595	213,4	1,68	177,8	137,2	0,62
Greece - Obj. 1 regions	13	5,0%	28048	1172,0	3,02	21,8	27,9	0,38
Italy - Obj. 1 regions	7	4,5%	33939	316,7	2,11	42,4	39,5	0,44
Portugal - Obj. 1 regions	7	3,9%	22305	3150,7	2,04	17,0	32,4	0,37
Spain - Obj. 1 regions	11	3,4%	36335	659,4	2,79	38,4	29,0	0,40
Other EU15 Obj. 1 regions*	7	4,4%	31908	268,3	1,82	211,0	182,1	0,55

* of which: 1 region of Netherlands, 1 of Austria, 1 of Belgium, Ireland and 3 of the United Kingdom

** data refer to 1999

Source: Our elaboration on Eurostat and European Commission

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Table 3: One-step and two-step GMM-DIFF and GMM-DSYS estimates of the dynamic unconditional convergence model - 206 EU15 regions

Estimation method	ρ	β	Implicit λ
GMM-DIFF One-step	-0,007 (0,038)	-0,061* (0,008)	0,063
GMM-DIFF Two-steps	-0,007* (0,003)	-0,061* (0,001)	0,063
GMM-SYS One-step	0,040 (0,041)	-0,025* (0,011)	0,025
GMM-SYS Two-steps	-0,005* (0,013)	-0,030* (0,004)	0,030

Note: Estimated Standard Errors below the estimated values; * statistically significant at the 5% level

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Table 4: One-step and two-step GMM-DIFF and GMM-SYS estimates of the dynamic conditional convergence model, equation (6) - 206 EU15 regions

Estimation method	ρ	β*	χ	φ_0	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6	φ_7	φ_8
GMM-DIFF One-step	0,015 (0,039)	-0,093* (0,016)	-0,045* (0,015)	-0,023 (0,022)	0,073* (0,017)	0,043* (0,013)	-0,039* (0,012)	0,033 (0,025)	-0,014* (0,007)	-0,001 (0,003)	0,003 (0,003)	-0,029 (0,021)
GMM-DIFF Two-steps	0,010* (0,005)	-0,090* (0,005)	-0,048* (0,008)	-0,022* (0,004)	0,071* (0,008)	0,043* (0,003)	-0,040* (0,003)	0,034* (0,005)	-0,012* (0,005)	-0,001* (0,0005)	0,003* (0,001)	-0,028* (0,003)
GMM-SYS One-step	0,048 (0,042)	-0,135* (0,031)	-0,105 (0,099)	-0,042 (0,043)	0,061* (0,030)	0,012 (0,017)	-0,002 (0,013)	0,102 (0,069)	-0,003 (0,012)	-0,001 (0,003)	0,006 (0,006)	-0,046* (0,023)
GMM-SYS Two-steps	0,019 (0,016)	-0,105* (0,010)	-0,086* (0,024)	-0,010 (0,010)	0,051* (0,011)	0,014* (0,005)	-0,007 (0,005)	0,023 (0,024)	-0,011* (0,004)	0,001 (0,002)	0,002 (0,002)	-0,018* (0,008)

Note: Estimated Standard Errors below the estimated values; * statistically significant at the 5% level

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Table 5: One-step and two-step GMM-DIFF and GMM-SYS estimates of the implicit parameters

Estimation method	α	λ	ϕ_0	ϕ_1	ϕ_2	ϕ_3	ϕ_4	τ_1	τ_2	τ_3	τ_4
GMM-DIFF One-step	0,487	0,049	-0,505	1,619	0,935	-0,861	0,741	-0,300	-0,018	0,075	-0,645
GMM-DIFF Two-steps	0,540	0,042	-0,445	1,450	0,888	-0,817	0,687	-0,249	-0,027	0,067	-0,573
GMM-SYS One-step	0,778	0,030	-0,399	0,587	0,115	-0,018	0,975	-0,030	-0,010	0,058	-0,443
GMM-SYS Two-steps	0,820	0,019	-0,119	0,596	0,169	-0,086	0,274	-0,132	0,003	0,022	-0,214

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Table 6: Tests of autocorrelation (LM) and over-identifying restrictions (Sargan)

	Test of first-order autocorrelation (LM test)	Test of second-order autocorrelation (LM test)	Test of over- identifying restrictions (Sargan test)
GMM-DIFF			
One-step	-8.802*	-0.889	1.128
Two-steps	-8.774*	-0.964	1,121
GMM-SYS			
One-step	-6.844*	0.527	3.509
Two-steps	-6.452*	0.882	3.096

Note: * statistically significant at the 5% level

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Table 7: Elasticities of investment rate (s_0) and steady-state growth rate ($\hat{Y}$) with respect to policy treatment (M_s) computed at the sample mean by regional group

Elasticity	GMM-DIFF (1-step)	GMM-DIFF (2-steps)	GMM-SYS (1-step)	GMM-SYS (2-steps)
$\varepsilon^{i}_{s,M}$				
All EU15 Obj. 1 regions	0,067	0,044	0,145	0,068
France - Obj. 1 regions	0,371	0,337	0,339	0,149
Germany - Obj. 1 regions	0,008	-0,034	0,049	0,075
Greece - Obj. 1 regions	-0,030	-0,028	0,142	0,018
Italy - Obj. 1 regions	0,039	0,016	0,117	0,062
Portugal - Obj. 1 regions	0,176	0,149	0,188	0,102
Spain - Obj. 1 regions	-0,001	-0,013	0,139	0,040
Other EU15 Obj. 1 regions	0,126	0,064	0,085	0,124
$\varepsilon^{i}_{\hat{Y},M}$				
All EU15 Obj. 1 regions	0,064	0,052	0,508	0,311
France - Obj. 1 regions	0,351	0,395	1,184	0,678
Germany - Obj. 1 regions	0,008	-0,040	0,171	0,343
Greece - Obj. 1 regions	-0,029	-0,032	0,495	0,083
Italy - Obj. 1 regions	0,037	0,019	0,410	0,285
Portugal - Obj. 1 regions	0,167	0,174	0,658	0,464
Spain - Obj. 1 regions	-0,001	-0,015	0,486	0,183
Other EU15 Obj. 1 regions	0,119	0,075	0,297	0,567

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[1] 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 a region-specific steady-state level, whereas club convergence implies multiple steady-state equilibria, one for any group (club) of regions.

[2] Besides β-convergence, the alternative concept of σ-convergence has been proposed (Barro and Sala-I-Martin, 1992; Quah, 1996). Whereas the former deals with the expected value of income growth conditional on its initial value, the latter concerns its statistical distribution across regions, over time or both. β-convergence is a necessary but not sufficient condition to have σ-convergence.

[3] According to the European Commission (2001, p. 131), "transfers from the structural funds added directly to demand and economic activity, but more importantly, since they were concentrated on investment […], they were aimed at increasing growth potential in the medium and long-term. […] The estimates of the "supply-side" effects on growth […] become predominant in the long-term. […] Although structural policies are ultimately judged in terms of their effect in narrowing regional disparities in GDP per head of employment, it is their impact on the underlying factors which determine economic development which is prime consideration."

[4] A more complete picture on the whole set of issues, as well as approaches, about the EU structural policy evaluation can be found in Bachtler and Wren (2006).

[5] In particular, Rodriguez-Pose and Fratesi (2004) provide further interesting details in this respect.

[6] We acknowledge the interesting suggestions and critical remarks made by an anonymous referee on the detailed representation of Objective 1 SF in the adopted model. They have been particularly helpful in improving a previous version of the model.

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[7] Alternatively, as clarified in the fourth section, the region-specific term may be random.

[8] Since T is always positive and largely >1, for simplicity we assume that when T=0 then ln$T$=0.

[9] The assumption is made that s_i remains constant, if not shocked by M, and its observed initial level corresponds to the steady-state level.

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

[11] The current NUTS classification actually comprises 211 NUTS II regions, but, owing to data availability, Ireland and NUTS I German regions Sachsen and Sachsen-Anhalt are included as single NUTS II regions.

[12] Badinger *et al*. (2002) assume a much higher value (0,25). In the present case, however, different values of this term do not relevantly affect the estimation results.

[13] For extensive information on data sources and treatment, including the regional attribution of multiregional funds, see Bussoletti (2004).

[14] This variable can be computed only for year 1999; thus, the 1999 value has been maintained over the whole 1989-2000 period. This assumption seems acceptable taking into account that infrastructural indicators usually show very little variations over time.

[15] As suggested by an anonymous referee, different groupings of Objective 1 regions could be proposed to interpret the mentioned differences. Nonetheless, clustering Objective 1 regions by country remains the most meaningful solution, as the country-effect still strongly conditions the regional performance. Results computed and reported by regional clusters, however, do not imply club convergence. In the conditional convergence approach here adopted, any region has its own steady-state, though groups of regions may show similarities in how conditioning variables affect it.

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[16] Although it is out of the 1994-1999 programming period, year 2000 is included in the sample period in order to take account of the growth effect of the last year of payments (1999).

[17] Nevertheless, several empirical studies suggest that, in finite samples, the two-step 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, 2003; Gaduh, 2002; Judson and Owen, 1999).

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

[19] This statistic is distributed as chi-square under the null hypothesis 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.

[20] Both statistics are distributed as standard normal under the null hypothesis of no serial correlation.

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