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Meta-analysis of the impact of European Union Structural Funds on regional growth

Sandy Dall'Erba[a] and Fang Fang[b]

ABSTRACT

Meta-analysis of the impact of European Union Structural Funds on regional growth. *Regional Studies*. This paper offers a meta-regression analysis of the controversial impact of European Union Structural Funds on the growth of the recipient regions. It identifies the factors that explain the heterogeneity in the size of 323 estimates of their impact recorded in 17 econometric studies. Heterogeneity comes from the publication status, the period examined, the control of endogeneity and the presence of several regressors, but not from differences in functional forms.

KEYWORDS

meta-analysis; hierarchical model; multivariate regression; regional growth; structural funds; public policy

摘要

欧盟结构基金对区域成长的影响之统合分析，*Regional Studies*。本文对欧盟结构基金对其接收区域的成长带来之争议性影响，提供一个统合性迴归分析。本文指认十七个计量经济研究所记载的三百二十三个影响规模的异质性之解释因素。异质性来自于公布情形、检视时期，对于内生性的控制，以及若干迴归因子的存在，但却非来自于功能形式的差异。

关键词

统合分析; 阶层式模型; 复迴归; 区域成长; 结构基金; 公共政策

RÉSUMÉ

Une méta-analyse de l'impact des Fonds structurels de l'Union européenne sur la croissance régionale. *Regional Studies*. Cet article présente une méta- analyse de régression de l'impact controversé des Fonds structurels de l'Union européenne sur la croissance des zones bénéficiaires. On identifie les facteurs susceptibles d'expliquer l'hétérogénéité de l'importance des 323 estimations de leur impact enregistrées dans 17 études économétriques. L'hétérogénéité s'explique par le statut de publication, par la période considérée, par la maîtrise de l'endogénéité et par la présence de plusieurs variables explicatives, mais non pas par les différences de formes fonctionnelles.

MOTS-CLÉS

méta-analyse; modèle hiérarchique; régression à plusieurs variables; croissance régionale; fonds structurels; politique publique

ZUSAMMENFASSUNG

Metaanalyse der Auswirkungen der Strukturfonds der Europäischen Union auf das Regionalwachstum. *Regional Studies*. Dieser Beitrag enthält eine Metaregressionsanalyse der umstrittenen Auswirkungen der Strukturfonds der Europäischen Union auf das Wachstum in den Empfängerregionen. Wir identifizieren die Faktoren zur Erklärung der heterogenen Größen der in 17 ökonometrischen Studien verzeichneten 323 Schätzungen der Auswirkungen. Die Heterogenität lässt sich auf den Publikationsstatus, den untersuchten Zeitraum, die Berücksichtigung von Endogenität und die Präsenz mehrerer Regressoren, nicht aber auf Unterschiede in den funktionellen Formen zurückführen.

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SCHLÜSSELWÖRTER
metaanalyse; hierarchisches Modell; multivariate regression; regionalwachstum; strukturfonds; öffentliche Politik

RESUMEN
Metaanálisis del impacto de los fondos estructurales de la Unión Europea en el crecimiento regional. *Regional Studies*. Este artículo contiene un análisis de metarregresión del impacto controvertido de los fondos estructurales de la Unión Europea en el crecimiento de las regiones receptoras. Identificamos los factores que explican la heterogeneidad del tamaño de 323 estimaciones de su impacto que se registraron en 17 estudios econométricos. La heterogeneidad procede del estado de la publicación, el periodo examinado, el control de la endogeneidad y la presencia de varios regresores, pero no de las diferencias en las formas funcionales.

PALABRAS CLAVES
metaanálisis; modelo jerárquico; regresión multivariada; crecimiento regional; Fondos estructurales; política pública

JEL C30, O47, R58
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INTRODUCTION

In the European Union every programming period sees around one-third of the budget devoted to various regional cohesion policies. Since their implementation in the 1970s, a large set of studies measure their impact on the economy of the recipient localities, regions and countries. They are selected because of their low levels of relative per capita gross domestic product (GDP), high unemployment rate, low density and recessive industry. While some contributions in the academic literature are generally supportive of the continuation of such policies (e.g. Cappelen, Castellacci, Fagerberg, & Verspagen, 2003; Esposti & Bussoletti, 2008), others cast doubts on their actual efficacy (e.g. Dall'Erba & Le Gallo, 2008; and some estimates of Dall'Erba & Le Gallo, 2007, and Bouayad-Agha, Turpinn, & Védrine, 2011), highlight their conditional efficacy (e.g. Dall'Erba & Le Gallo, 2007; Ederveen, Gorter, De Mooij, & Nahuis, 2002; Ederveen, De Groot, & Nahuis, 2006; Rodriguez-Pose & Fratesi, 2004), or conclude that they act negatively on growth (Fagerberg & Verspagen, 1996; and some estimates of Puigcerver-Peñalver, 2007, and Bouayad-Agha et al., 2011). Understanding what factors explain the differences in the estimated impact of regional policies and whether actual practical changes can be implemented is especially important now that sluggish economic growth among European Union members and recent rounds of bailouts have undermined the availability of public funding for regional cohesion purposes.

This paper relies on a literature that econometrically estimates the regional growth impact of Structural Funds and identifies the sources of heterogeneity in the estimated impact. The focus is solely on econometric studies for homogeneity purposes. Moreover, some other papers are not considered because they do not rely on a sufficiently homogenous definition of the funds (e.g. they use proxy or dummies). As a result, the meta-database is composed of 17 manuscripts offering 323 estimates in total. The meta-analysis framework was first introduced by Glass (1976). It has the capacity to combine the results of several existing studies and summarize their outcome. In addition, it controls for differences/similarities within and between studies and identifies whether the former come from sampling (e.g. size and time period of the sample) or non-sampling (e.g. estimation process and regressors used) characteristics. Estimation takes place in the frame of meta-regressions that measure the role of the study characteristics by explaining the differences among study outcomes. Hence, it allows a more complete picture of an existing literature than traditional qualitative or narrative approaches.

The paper is organized as follows. The second section begins with a short description of the theory commonly used to measure the impact of European Union Structural Funds. It continues with a description of some of the econometric challenges met in this literature. The third section reports the way the primary estimates were collected from the existing literature. The fourth section presents the meta-regression models as well as the selected moderators. The fifth section reports the estimation results and discusses the factors that significantly affect the magnitude of the estimated impact of the funds. In addition, an ordered probit model uncovers the factors that influence the probability of estimating a significantly positive return of the funds. Finally, the sixth section concludes.

GROWTH THEORIES AND ECONOMETRIC METHODS

Theories

Three strands of economic growth theory are commonly used to understand the role of public investments in stimulating growth. The traditional approach is the neoclassical growth framework that relies on the assumptions of decreasing returns to capital and constant and exogenous rate of technological progress. Structural Funds correspond to public investments allocated to a capital-scarce region, hence they increase the growth rate of the recipient area that experiences faster convergence towards its steady-state level but for a short period of time only (Solow, 1956). The growth rate does not change in the long run due to the decreasing nature of the returns to capital. This holds true with investments in human capital as well (Mankiw, Romer, & Weil, 1992). In this framework, only changes in the exogenous rate of technological progress modify the steady-state growth rate. The second strand of the literature, the endogenous growth theory, is based on the assumptions of constant returns to capital (at the regional level), endogenous technological progress and local externalities. It assumes that new investments in public capital increase the marginal product of private capital. This fosters capital accumulation and growth in the recipient region in the long run (Aschauer, 1989; Romer, 1990). However, the empirical paradox pinpointed by Jones (1995a, 1995b) according to which total factor productivity remains constant in spite of new expenditure in research and development (R&D) and human capital has given birth to semi-endogenous growth theory (Jones, 1995b). Based on the idea of decreasing returns to scale in the production of knowledge, these models assume that total factor productivity growth depends on the exogenous growth rate of the population because it determines the R&D employment growth rate.

Neither the neoclassical nor the endogenous growth theories are specific enough about the type of public capital that is funded, yet the largest share of Structural Funds (around one-third) finances transportation infrastructures. They reduce transportation costs, hence they have consequences on the economic growth of the recipient regions in ways that cannot be captured in any of the previous growth theories. As such, the third strand of economic growth theory, namely the new economic geography (Fujita, Krugman, & Venables, 1999; Krugman, 1991), has generated increasing interest. In this framework, new transportation infrastructures lead to different degrees of improvement in accessibility and economic development in the region(s) where they are implemented (Vickerman, Klaus, & Wegner, 1999). When new (interregional) transportation infrastructures connect regions of different levels of income, companies and workers may de-locate from the poor region to the rich one to benefit from agglomeration economies (Krugman, 1991). This process can be self-reinforcing when the presence of localized technology spillovers is conducive to growth, as indicated in the models of Baldwin, Forslid, Martin, Ottaviano, and Robert-Nicoud, (2004) who combine new economic geography and endogenous growth theories. In addition, since interregional transportation infrastructures are more often the rule than the exception in Europe, they will increase the accessibility of several regions, but the gains they generate will always be relatively higher in the richest one (Vickerman et al., 1999).

Econometric methods

In spite of these three strands of economic growth theory, the empirical literature of interest here relies almost exclusively on the neoclassical beta- convergence model à la Barro and Sala-i-Martin (1991). This feature is an advantage in a meta-analysis as it makes the estimates of the primary studies homogeneous conceptually. Specifically, the (cross-section) model most commonly used in the literature to measure the elasticity of the funds derives from the beta-convergence model specified in Mankiw et al. (1992, p. 423) but with variations in the number and specification of the regressors:

$$\begin{aligned}
&\frac{1}{T-t_0}(\ln(y_T)-\ln(y_{t_0}))=g\\
&=\alpha\iota_n+\beta_0\ln(y_{t_0})+\beta_1\ln(s)+\beta_2\ln(n+g+\delta)\qquad(1)\\
&+X\beta_3+\beta_4\mathrm{SF}+\varepsilon\\
&\text{with}\qquad \varepsilon\sim N(0,\sigma_\varepsilon^2 I_n)
\end{aligned}$$

where the dependent variable is the annual growth rate of per capita GDP in region i over the period $t_0 - T$; y_{t_0} is the initial level of per capita GDP; s is the average gross domestic savings rate; n is the population growth rate; g is the exogenous rate of technological progress; δ is the rate of depreciation; X is a matrix of additional variables that maintain the steady state of each economy constant; SF is Structural Funds; and ε is the error term with the usual properties. Most studies report a significant negative estimate of β_0, which validates the convergence assumption brought to the fore by the neoclassical growth model. This paper focuses on the effect size of the average annual growth rate with respect to Structural Funds, i.e. the coefficient β_4.

Note that one gets a different marginal effect when an interaction term is added to specification (1). For instance, when Ederveen et al. (2006) evaluate whether the funds are *conditionally* effective on the quality of the institutions that rule the recipient region, they add a term such as β_5SF$*$ institutions to the regressors of equation (1). The marginal effect then becomes $\partial g/\partial\mathrm{SF} = \beta_4 + \beta_5$ institutions. In this situation, the effect at the mean of the interacted term is measured when possible (e.g. the mean of '*institutions*' in the case above).

While most of the studies measure the variables in the matrix X at the initial time period to prevent endogeneity, the funds are sometimes measured over the growth period. This leads to a problem of reverse causality as the funds are partially allocated based on past relative levels of regional per capita income (Dall'Erba & Le Gallo, 2008). The more recent studies in the database have dealt with this issue by using past levels of Structural Funds (such as Mohl & Hagen, 2010), instrumental variables (such as Dall'Erba & Le Gallo, 2008) or Arellano and Bond's (1991) estimator (Esposti & Bussoletti, 2008). Differences in the treatment of endogeneity among primary studies will be treated below.

As access to Structural Funds data has become more available, several authors have decided to assess the impact of the funds in the frame of a panel data model. Such a specification provides them with more information and data variability. This allows control over unobserved heterogeneity and reduces problems of collinearity among the explanatory variables. No panel-data study uses a random effect approach, which, in the frame of a neoclassical growth model, implies that the individual effects are correlated with some regressors. This would lead to endogeneity (Esposti & Bussoletti, 2008).

Increasing interest in new economic geography and advances in the field of spatial econometrics have led four studies to investigate the impact of the funds on both the targeted regions and their neighbours (Bouayad-Agha et al., 2011; Dall'Erba & Le Gallo, 2007, 2008; Mohl & Hagen, 2010). It allows them to proxy for interregional backward and forward linkages, technology spillovers, commuting across regions, and to refute the traditional assumption of independence of the error terms.

PRIMARY STUDIES

The collection process of the primary studies was performed to avoid missing any relevant empirical estimates and to reduce the potential biases due to any non-random selection. The following process was adopted: first, a search was made on the Economic Literature Index, ISI web of Knowledge and Google for any reference such as 'European growth', 'Structural Fund' and 'European regional cohesion'. Next, only the studies written in English were selected as the authors have limited capacity to extract information from other studies. Studies using proxies for Structural Funds were eliminated. The studies using dependent variables other than per capita income growth, using a theoretical framework other than the neoclassical growth model or relying on a different modelling framework were also eliminated. Some studies and measurements were also removed because they do not use the actual amounts of Structural Funds. For instance, some use a binary variable for recipients versus non-recipients (Becker, Egger, & Von Ehrlich, 2010; Esposti, 2007) or use different growth regressions by eligibility status (Ramajo, Márquez, Hewings, & Salinas, 2008). Here, only the measurements of Esposti (2007) based on the actual allocation of the funds are kept. The latter contribution demonstrates clearly that using a dummy variable or actual expenses leads to different results.

Furthermore, some estimates in Puigcerver-Peñalver (2007) were disregarded because they are based on the regional allocation of the funds relatively to the Community average. Note also that econometric studies providing local estimates, as Le Gallo, Dall'Erba, and Guillain (2011), or focusing on the regions of one country only could not be considered since all the other studies measure the overall impact on the sample of European Union regions.

Studies that appear in the bibliography of the relevant articles were individually checked too. Working papers that have led to a publication have naturally been removed from the sample. It leads to a meta-database composed of 17 studies, of which two had estimates calculated over a five-year growth process that needed to be adjusted to a *yearly* growth rate. Secondly, the functional forms needed more homogeneity. While most of the studies rely on a linear model or on a log–log model (nine and five articles respectively), two articles use a log–lin model and one uses a lin–log model. The latter two cases report few estimates and the semi-elasticity they represent $((\Delta Y/Y)/\Delta X)$ or $\Delta Y/(\Delta X/X)$ can be transformed to an elasticity $((\Delta Y/Y)/(\Delta X/X))$ when the average value of X (for log–lin) or Y (for lin–log) is reported. This process guarantees the completeness, homogeneity and comparability of the population under investigation, i.e., 323 estimates of the impact of Structural Funds on regional growth. The studies used in the meta-database and some of the characteristics of the collected estimates appear in Table 1.

Among them, 77 are marginal effects based on an interaction term such as $\partial\,\mathrm{growth}/\partial\mathrm{SF} = \beta_4 + \beta_5 z$. Since the primary studies report the measurement of the mean of the interacted term z in 65 cases, the total effect evaluated at the mean is β_4 in 258 cases and it is $\beta_4 + \beta_5 z$ in 65 cases.

FIXED-EFFECTS MODEL, MIXED-EFFECTS MODEL AND HIERARCHICAL MODEL

The fixed effects and mixed effects regression models are commonly used in meta-analysis to control for the heterogeneity in the primary estimates. The fixed effects model assumes that the variability among the effect sizes can be fully explained by a set of moderators that account for differences in the characteristics across study i:

$$T_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \varepsilon_i \\ \text{with } \varepsilon_i \sim N(0, \mathrm{v}_i) \tag{2}$$

where $x_1, \ldots, x_k$ are the study characteristics; $\beta_1, \ldots, \beta_k$ are the regression coefficients; ε_i is the error term; v_i is the estimated variance of the effect sizes collected from the primary studies; and $i = 1, 2, \ldots, k$ are indices for the estimated effect sizes.

In the mixed effect model the variability beyond the sampling error is derived partly from a systematic factor and partly from random sources:

$$T_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \mu_i + \varepsilon_i \\ \text{with} \quad \varepsilon_i \sim N(0, v_i) \text{ and } \mu_i \sim N(0, \tau^2) \tag{3}$$

Both the fixed- and the mixed-effects models allow the true effect size and its precision to vary across regressions. However, the mixed effects model also assumes that not all heterogeneity is observable. It allows for the presence of residual heterogeneity by assuming that the underlying effects follow a normal distribution around the effects predicted by the covariates (Sutton, Abrams, Jones, Sheldon, & Song, 2000).

One potential drawback of the above models is their assumption that the estimated effect sizes are independently distributed no matter from which study they derive. The traditional assumption of independence can be violated when two (or more) effect size estimates come from the same study. This means they are based on the same sample of data, which introduces dependence at the sampling level, but it can easily be accounted for by appropriate estimation of the sampling covariance matrix. Here, the 323 observations in the meta-analysis database are not

Table 1. Characteristics of the primary studies.

Study	Publication type	Number of estimates	Functional form	Effect size estimate						
				Minimum	Maximum	Mean	SD	Percentage significant and negative	Percentage non-significant	Percentage significant and positive
Akçomak (2008)	T	12	Lin–lin	0.004	0.080	0.044	0.029	0.0	91.7	8.3
Bähr (2008)	PP	13	Lin–lin	−0.001	0.157	0.063	0.040	0.0	38.5	61.5
Beugelsdijk and Eijffinger (2005)	PP	4	Lin–lin	−1.431	0.320	−0.258	0.815	0.0	75.0	25.0
Bouayad-Agha et al. (2011)	PP	18	Log–log	−0.005	0.020	0.006	0.008	16.7	83.3	0.0
Bouvet (2005)	T	4	Log–log	0.020	0.270	0.105	0.113	0.0	25.0	75.0
Cappelen et al. (2003)	PP	3	Lin–lin	0.005	0.007	0.006	0.001	0.0	0.0	100
Dall'Erba and Le Gallo (2008)	PP	3	Lin–lin	−0.010	0.002	−0.004	0.006	0.0	100	0.0
Dall'Erba and Le Gallo (2007)	PP	28	Lin–lin	−0.002	0.007	0.000	0.002	14.3	71.4	14.3
Ederveen et al. (2002)	WP	3	Log–lin	−0.350	0.700	0.123	0.533	33.3	33.3	33.3
Ederveen et al. (2006)	PP	31	Log–log	−0.026	0.062	0.008	0.022	0.0	100	0.0
Esposti (2007)	PP	8	Lin–lin	0.000	0.000	0.000	0.000	0.0	62.5	37.5
Esposti and Bussoletti (2008)	PP	4	Log–log	0.139	0.414	0.226	0.129	0.0	100	0.0
Fagerberg and Verspagen (1996)	PP	2	Lin–lin	−0.417	−0.225	−0.321	0.136	100	0.0	0.0
Mohl and Hagen (2010)	PP	90	Log–log	−0.009	0.011	0.000	0.004	18.9	54.4	26.7
Puigcerver-Peñalver (2007)	PP	6	Log–lin	−1.343	0.001	−0.448	0.602	50.0	50.0	0.0
Rodriguez-Pose and Fratesi (2004)	PP	92	Lin–lin	−7.586	6.294	0.484	2.184	3.2	85.9	10.9
Rodriguez-Pose and Novak (2013)	PP	2	Lin–log	0.021	0.369	0.195	0.247	0.0	50.0	50.0
Total		323		−7.586	6.294	0.174	1.504	10.2	71.5	18.3

Note: PP, published paper; WP, working paper; T, thesis.

from 323 independent studies since they are all nested within 17 studies. In order to verify if accounting for this type of dependence modifies the conclusions, the above models are complemented with a two-level hierarchical model that considers, first, the within-study variation and, second, the between-study variation (Goldstein, 2003).

Following the notation used by Dominicis, Florax, and De Groot (2008), the two-level hierarchical model is:

$$T_{ij} = \beta_{0j} + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \varepsilon_{ij},$$

$$\beta_{0j} = \beta_0 + \mu_j, \text{ with } \varepsilon_{ij} \sim N(0, \text{ v}_i) \text{ and } \mu_j \sim N(0, \tau^2)$$

where i is the individual observations nested in study j; ε_{ij} represents the error term at measurement level; v_i is the estimated variance of the effect sizes from the collected studies; and μ_j is the error term at the study level shared by all measurements within the same study.

As in Dobson, Ramlogan, and Strobl (2006), this paper finds that it would be impossible to take into account all the conditioning variables given the limited size of the sample and that several of them can be found in some individual studies only. As a result, the focus is on the most commonly used conditioning variables, while differences in data and estimation characteristics are captured by dummies. Controlling for all sources of heterogeneity is anyway unnecessary as it would only capture study differences that are already taken into account in the study fixed effects of the hierarchical model.

There are three classes of moderators. The first class concerns the *data characteristics*, which include information about the following:

- The publication status (published or unpublished), as it may be a source of heterogeneity (Egger, Davey Smith, Schneider, & Minder, 1997).
- The degree of freedom.
- The area of study (more or less than EU-12) as studies performed on a sample that excludes the Southern and East European countries generally conclude to a greater degree of cohesion and efficiency of the funds.
- The type of spatial unit used (country versus regions) as it is well known that the spatial scale used for the analysis influences the conclusions.
- The definition of the funds (fund/GDP versus other) in order to differentiate the ways the primary studies normalize the allocation of the funds.
- The functional form used (linear, semi-elasticity versus elasticity) as the three forms are found in the primary studies. These two functional forms constitute the bulk of the estimates (Table 1).
- Whether the funds are for Objective 1 regions as historically the largest share of Structural Funds has been allocated to so-called Objective 1 regions selected upon their level of per capita GDP being below 75% of the European average.
- The time lag between the average allocation of the funds and the average of the growth period as several primary studies use a lag to remove potential problems of simultaneous causation and recognize that public investments do not act instantaneously on growth.
- The number of years included in the allocation of the funds. Studies based on an average of several years are less sensitive to the cyclical effect of each year's allocation.
- Initial year of the growth period (pre- versus post-1994). It allows one to test the existence of a structural break in the capacity of the funds to promote growth. The year 1994 is chosen as it corresponds to the beginning of the 1994–99 programming period during which more than 2.5 times the previous (1989–93) level of funds was allocated.
- Whether the study was written/published before or after the median year (2007) of the sample. This variable allows one to test whether more recent studies benefit from the experience built in the past literature. For instance, more recent studies pay a much greater degree of attention to issues of endogeneity of the funds and spatial autocorrelation than earlier studies. If not controlled for, both issues affect the magnitude and precision of the estimates.

The second class of moderators concerns the *estimation characteristics*, that is information on the estimation methods. Distinguishing the least squares methods – ordinary least squares (OLS), generalized least squares (GLS), least squares dummy variable (LSDV) – from the others – maximum likelihood (ML), generalized method of moments (GMM), two-stage least squares (2SLS) – is necessary. While OLS and ML are equivalent in most simple regressions, they are not equivalent in the presence of spatial autocorrelation. This means ML is not part of the reference group. The other two moderators in this class indicate whether instrumental variables (IV) were used to account for the endogeneity of the funds and whether a fixed effect approach was used. As mentioned above, panel data studies cannot use a random effect approach in a neoclassical growth model. Finally, the role of controlling for spatial dependence is tested as it is increasingly recognized that the funds have effects beyond the boundaries of the recipient areas. It is a dummy with value 1 when the presence of externalities and feedback effects has been accounted for by spatial econometric means in the primary study.

The third class of moderators refers to the *presence of regressors* other than Structural Funds. The estimated effectiveness of the funds is also conditional upon such characteristics in the primary studies (Ederveen et al., 2002, 2006; Esposti & Bussoletti, 2008; Rodriguez-Pose & Fratesi, 2004). They include the presence/absence of a national dummy variable, of the initial per capita GDP, of variables capturing the characteristics of the economic structure (e.g. share of workers in agriculture), employment or population, public investments or infrastructure stock, human capital or investments in education or research and development, corruption/institutional quality and the presence of an interaction term.

In essence, the results will suggest that the use of the above data characteristics, estimation characteristics and moderators produce smaller/greater estimates of β_4 on average in the primary studies. Except for the few continuous variables present here, the estimates can also be understood as measuring the bias that exist from excluding the associated control or choosing the alternative (in parentheses in Table 2) in the primary study.

Note that the interpretation of some of the above dummy variables is not necessarily the same for different studies. For example, which country- or region-specific characteristics are captured by 'fixed effects' depends on which other regressors are already included in the primary study. Similarly, the type of IV used is conditional upon other existing regressors. However, it is impossible to account for such a large degree of heterogeneity across primary studies without compromising the degree of freedom and the quality of the estimates.

META-REGRESSION RESULTS

Table 2 presents the results of the regressions for the fixed effect model (column 1) and the mixed effect model (column 2) where the 323 estimates are considered independent and for the hierarchical linear model where they are not (column 3). Indeed, the study fixed effects included in the latter model controls for differences across studies.

The magnitude, sign and precision level of the estimates are comparable across all three models. The results indicate that the first significant moderator is 'publish'. It is a dummy variable that takes 1 when the primary study is published, and 0 if not. The coefficient indicates that, on average, published studies report an impact that is lower than unpublished studies. The second significant moderator is 'area of study'. It is a dummy variable that takes the value 1 when the area of study is less than EU-12, and 0 if not. The coefficient indicates that, on average, the impact of the funds on growth is greater in samples considering 'less than EU-12' countries than in samples based on 'EU-12 or more' countries. This result is not surprising considering that the poor regions of the Southern countries that enlarged the European Union from nine to 12 members consumed a large share of the Structural Funds, yet they did not necessarily catch up with their average national income or with the European average (Dall'Erba & Le Gallo, 2008). While no significant difference between studies performed at the country or regional level is found, there is one between estimates based on the funds/GDP versus any other form of normalization (funds/population or just funds). The former leads to estimates that are slightly higher on average.

No significant difference due to the functional form is found, which supports the choice of working with the whole sample. The next significant moderator is 'Objective 1'. It is a dummy variable that takes value 1 when the funds are explicitly allocated to Objective 1 regions. The difference in the estimated impact of such funds compared with non-Objective 1 funds is significant but is very small (less than 0.000). The results indicate also that the immediate impact of the funds is greater than its delayed impact, although not by much. This argument is in tune with Boldrin and Canova (2001) where these authors see, at least in the first rounds of European Union cohesion policies, a strategy targeted more towards short-term income support and redistribution than long-term sustainable development. The number of years included in the allocation of the funds has no significant impact on heterogeneity. However, both the initial year of the growth period and the year of composition/publication of the primary study matter. They are dummy variables with value 1 for early periods and 0 for the more recent periods. Several factors could explain the role of the beginning of the growth period: the presence of business cycles that render the funds more efficient over some periods of time, an increase in the amounts allocated over each programming period (following the enlargement to the South, the 1994–99 period saw a significant increase in funding for regional development compared with the past), or the presence of a 'learning effect' in the allocation and use of the funds as advanced by Rodriguez-Pose and Novak (2013) recently. The authors justify it with a 'more appropriate expenditure of the Cohesion funds, due to a progressive shift in their expenditure priorities' as well as a 'strengthening of the principle of partnership' with local and regional authorities (p. 32). The significant presence of a time trend in the year of publication or composition of the manuscript indicates a 'learning effect' too, although of a different nature. More recent studies can rely on a larger literature providing additional expertise on the topic and on the appropriate statistical techniques to which to pay attention, among others spatial autocorrelation and the endogenous nature of the funds. Both effects can affect the magnitude and the precision of the estimates.

Next, this paper tests whether several estimation characteristics used in the primary studies influence the estimated impact of the funds on growth. It appears that controlling for the endogeneity of the funds leads to estimates that are lower on average. It is the only significant characteristic in the second class of moderators.

Finally, the role of the regressors included in the primary studies is tested. They correspond to a dummy variable with value 1 when it is present in the primary study, and 0 otherwise. Three moderators are significant at the 5% level. They are 'human capital or investment in education or R&D', 'corruption/institutional quality' and 'interaction term'. The first variable leads to an effect size that is lower on average. Its presence across many studies reflects the dominance of the augmented Solow growth model that includes the presence of a proxy for human-capital accumulation (Mankiw et al., 1992). Ederveen et al. (2006) explore the role of the second variable the most among the four studies that do so. Not surprisingly, they conclude that the effectiveness of the funds is conditional upon the level of corruption/institutional quality of the recipient area. Compared with studies that do not control for this characteristic, their estimates conclude to a lower effect size on average. Finally, when it comes to the 'interaction term', the reader should refer to the primary studies to find the exact definition of the 17

Table 2. Meta-regression results.

Moderator variables	**Fixed effects**	**Mixed effects**	**Hierarchical**	**Ordered probit**
Constant	0.187	0.187	0.187	
	(0.003)	(0.003)	(0.003)	
Data characteristics				
Publication status: published (unpublished)	−0.047	−0.047	−0.047	1.453
	(0.045)	(0.045)	(0.045)	(0.052)
Degrees of freedom[a]	−0.001	−0.001	−0.001	0.726
	(0.180)	(0.178)	(0.180)	(0.081)
Area of study: less than EU-12 (EU-12 or more)	0.037	0.037	0.037	0.037
	(0.008)	(0.008)	(0.008)	(0.008)
Spatial units: country (regions)	0.006	0.006	0.006	0.914
	(0.560)	(0.562)	(0.560)	(0.377)
Fund definition: fund/gross domestic product (GDP) (other)	0.068	0.068	0.068	2.224
	(0.044)	(0.044)	(0.044)	(0.050)
Functional form: lin–lin (log–log)	−0.002	−0.002	−0.002	−2.502
	(0.639)	(0.639)	(0.639)	(0.022)
Functional form: semi-elasticity (log–log)	0.003	0.003	0.003	−1.948
	(0.912)	(0.913)	(0.912)	(0.014)
Recipient regions: Objective 1 regions (other)	0.000	0.000	0.000	0.100
	(0.002)	(0.003)	(0.002)	(0.606)
Time lag: number of years[a]	−0.001	−0.001	−0.001	0.253
	(0.000)	(0.000)	(0.000)	(0.004)
Years of allocation[a]	−0.001	−0.001	−0.001	0.186
	(0.826)	(0.826)	(0.826)	(0.083)
Initial year of growth period: pre-1994 (post-1994)	−0.098	−0.098	−0.098	−0.214
	(0.001)	(0.001)	(0.001)	(0.593)
Early study: written pre-2007 (recent study: written post-2007)	−0.026	−0.026	−0.026	−1.547
	(0.019)	(0.019)	(0.019)	(0.171)
Estimation characteristics				
Estimation method: other (least squares methods)	0.031	0.031	0.031	−1.817
	(0.341)	(0.341)	(0.341)	(0.066)
Endogeneity (no endogeneity)	−0.002	−0.002	−0.002	−0.250
	(0.001)	(0.001)	(0.001)	(0.355)
Fixed effects approach (no effect)	−0.023	−0.023	−0.023	0.334
	(0.348)	(0.348)	(0.348)	(0.611)
Spatial autocorrelation	−0.031	−0.031	−0.031	1.935
	(0.339)	(0.339)	(0.339)	(0.040)
Presence of regressors				
National dummy variable	0.000	0.000	0.000	−0.262
	(0.232)	(0.233)	(0.232)	(0.563)
Initial per capita GDP	−0.033	−0.033	−0.033	−0.506
	(0.494)	(0.494)	(0.494)	(0.328)
Economic structure	0.000	0.000	0.000	1.958
	(0.055)	(0.058)	(0.055)	(0.011)

(*Continued*)

Table 2. Continued.

Moderator variables	**Fixed effects**	**Mixed effects**	**Hierarchical**	**Ordered probit**
Employment or population	0.022	0.022	0.022	−2.025
	(0.307)	(0.307)	(0.307)	(0.006)
Public investment or infrastructure stock	−0.002	−0.002	−0.002	0.285
	(0.537)	(0.537)	(0.537)	(0.652)
Human capital or investment in education or research and	−0.102	−0.102	−0.102	−0.916
development (R&D)	(0.000)	(0.000)	(0.000)	(0.202)
Corruption/institutional quality	0.040	0.040	0.040	1.106
	(0.000)	(0.000)	(0.000)	(0.082)
Interaction term	0.010	0.010	0.010	0.863
	(0.000)	(0.000)	(0.000)	(0.086)
Threshold from 'Positive significant' to 'Negative significant'				−0.699
				(0.516)
Threshold from 'Negative significant' to 'Non-significant'				−0.274
				(0.799)
N	323			
Log-likelihood	473.392	0.163	473.392	−208.73
Akaike information criterion (AIC)	−896.785	0.163	−894.785	469.459
*R**	0.163	0.163	0.163	0.357

Note: The fixed effect model is estimated by maximum likelihood (ML); the mixed effect model is estimated by restricted ML; and the hierarchical model is estimated by iterative restricted ML. In the latter model, the level-1 number of estimates is 323; and the level-2 number of studies is 17. The ordered probit model is estimated by ML. All moderator variables enter the regression as dummies, except those labelled '[a]', which are continuous variables. The omitted category for dummy variable appears in parentheses below the name of the moderator variable. The *p*-values are reported in parentheses below the coefficient estimates.

variables with which the funds have been interacted in 77 cases. On average, the presence of an interaction term leads to a higher estimated impact of the funds in the primary studies.

When comparing the three models, it turns out that the coefficient estimates are very similar in magnitude and precision. It is confirmed in the similarity of the models' fit values (log-likelihood, Akaike information criterion (AIC) and R^* – the Pearson correlation test between the fitted and observed values) and can be explained by the value of τ^2 being zero in the mixed and hierarchical models.[1] As a result, the heterogeneity detected in the distribution of the effect sizes is entirely observable whether it comes from the differences in study design, estimation processes, moderators used in the primary studies or the variance of the effect sizes they estimate.

Finally, the above models are complemented by an ordered probit model that presents the advantage of accounting for *both* the effect size of the dependent variable and whether or not it is significant in the primary studies (Card, Jochen, & Weber, 2010). In this approach, the dependent variable takes on a value of 0 for the 'significant positive estimates' (when $T_i/\sqrt{v_i} > 1.96$), 1 for the 'significant negative estimates' (when $T_i/\sqrt{v_i} < -1.96$) and 2 for the 'non-significant estimates' (when $[|T] \downarrow / \sqrt{(v \downarrow i)}| <$ 1.96). In this model the errors are assumed to be normally distributed with variance 1 (Greene, 2012, p. 788). The results appear in the last column of Table 2. All the significant and negative estimated coefficients indicate the variables that increase Prob $(y = 0 \mid x)$. They also decrease Prob $(y = 2 \mid x)$ while their impact on the middle category, Prob $(y = 1 \mid x)$, is more ambiguous, as described in Greene (2012, p. 789). The opposite can be said about the significant and positive estimated coefficients. The results indicate that the variables that increase the probability of a positive and significant estimated impact of the funds are the use of a functional form other than elasticity and the presence of a variable controlling for the level of 'Employment or population' in the primary study. The probability of concluding to an efficient impact of the funds is found to decrease with increasing years of lag between allocation and growth, which indicates the immediate rather than long-run impact of European Union cohesion policies (Boldrin & Canova, 2001); when the funds are divided by GDP; when spatial autocorrelation is controlled for (Dall'Erba & Le Gallo, 2008); and when the original model captures the 'economic structure' of the recipient area.

CONCLUSIONS

The capacity of Structural Funds to promote regional economic growth has been controversial for decades. Both economic theory and empirical applications are not unanimous about their role on growth; yet Structural Funds are an important part of the European integration project and the evaluation of their impact matters for both the recipients and the payers. This paper takes stock of the large number of studies that measure econometrically the impact of the funds on growth and selects among them those that offer comparable effect sizes. It leads to 17 studies that offer 323 marginal effects.

The sources of their heterogeneity are examined by means of several weighted regression models (fixed-effects model, mixed-effects model and hierarchical model). While they all assume that part of the heterogeneity is due to differences in the data characteristics, estimation methods and choice of regressors in the primary studies, they each model the variance of the omitted variables differently. Yet, they all lead to very similar estimates, which proves the robustness of the results and that all the heterogeneity detected among the effect sizes is observable. They indicate that several differences in the data characteristics are at the origin of the heterogeneity found in the primary estimates. Among them, the publication status is found to influence the size of the estimates. A 'learning effect' is also present because studies focusing on more recent years conclude to a larger impact of the funds, which suggests the way of allocating and using them has become more efficient. Furthermore, the results indicate that the differences in functional forms used in the primary studies do not have a significant impact on the size of the estimates.

Controlling for endogeneity and for three types of regressors ('human capital or investment in education or R&D', 'institutional quality' and 'interaction term') in the original studies also lead to significant differences in the primary estimates. The latter are characteristics of the recipient regions that condition the effectiveness of the funds.

Finally, this study complements the usual meta- analytic approach by running an ordered probit model to uncover the factors that affect the probability of estimating a significantly positive impact of the funds. To the authors' knowledge, this endeavour had never been done before.

These results suggest that future researchers working on European Union regional development policies should be aware of the possible econometric bias and associated erroneous conclusions that come with their choice of study design and regressors. On the other hand, it is now clear that there are many aspects of the study such as the functional form and some estimation characteristics they should not be too worried about since they do not affect significantly the size of the estimates on average. In addition, future researchers will be able to rely on a larger literature pool than the first contributors to this field and this 'learning effect' has proven not negligible.

Given the long-lasting interest for improving the effectiveness of the funds, future contributions should devote more attention to estimating the impact of the funds in the frame of theories and models other than the neoclassical beta-convergence model. For instance, Dall'Erba, Guillain, and Le Gallo (2009) offer an approach based on an endogenous growth model, but many more contributions are needed. Another exciting development in the evaluation of the funds is the use of a counterfactual methodological approach based on the regression discontinuity design, as in (Becker et al. 2010; Becker, Egger, & Von Ehrlich, 2013) and Pellegrini, Terribile, Tarola, Muccigrosso, & Busillo (2013). The authors build on the allocation rule of Objective 1 funds to compare the effect on the regions with a per capita GDP level just below the eligibility threshold (75% of the European Union average) with the per capita GDP of the regions just above since they did not get this type of funding. Last but not least, more attention could be given to locally weighted estimates of the funds, as in Le Gallo et al. (2011). Their main contribution is to provide coefficient estimates for every single region, as opposed to the average impact for the entire sample, as is currently done in the literature. It helps them identify the regions where the funds have had a positive and significant impact and allows them to reconsider the 'one size fits all' approach that has dominated the allocation process and the empirical literature so far.

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NOTE

1. The hierarchical model shows the same results when the studies written by the same author(s) are considered as one. There are still 323 estimates in this case, but only 12 independent studies.

REFERENCES

Akçomak, S. I. (2008). *The impact of social capital on economic and social outcomes* (PhD dissertation). Maastricht University, Maastricht.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*, 277–297. doi:10.2307/2297968

Aschauer, D. A. (1989). Is public expenditure productive? *Journal of Monetary Economics*, *23*, 177–200. doi:10.1016/0304-3932(89)90047-0

Bähr, C. (2008). How does sub-national autonomy affect the effectiveness of structural funds? *Kyklos*, *61*, 3–18. doi:10.1111/j.1467-6435.2008.00389.x

Baldwin, R., Forslid, R., Martin, P., Ottaviano, G., & Robert-Nicoud, F. (2004). *Economic geography and public policy*. Princeton: Princeton University Press.

Barro, R. J., & Sala-i-Martin, X. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, *1991*, 107–182. doi:10.2307/2534639

Becker, S. O., Egger, P. H., & Von Ehrlich, M. (2010). Going nuts: The effect of EU structural funds on regional performance. *Journal of Public Economics*, *94*, 578–590. doi:10.1016/j.jpubeco.2010.06.006

Becker, S. O., Egger, P. H., & Von Ehrlich, M. (2013). Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects. *American Economic Journal: Economic Policy*, *5*, 29–77. doi:10.1257/pol.5.4.29

Beugelsdijk, M., & Eijffinger, S. C. W. (2005). The effectiveness of structural policy in the European Union: An empirical analysis for the EU-15 in 1995–2001. *Journal of Common Market Studies*, *43*, 37–51. doi:10.1111/j.0021-9886.2005.00545.x

Boldrin, M., & Canova, F. (2001). Inequality and convergence in Europe's regions: Reconsidering European regional policies. *Economic Policy*, *16*, 206–253. doi:10.1111/1468-0327.00074

Bouayad-Agha, S., Turpinn, N., & Védrine, L. (2011) Fostering the development of European regions: A spatial dynamic panel data analysis of the impact of cohesion policy. *Regional Studies 47*, 1573–1593. doi:10.1080/00343404.2011.628930

Bouvet, F. (2005). *European Union regional policy: Allocation determinants and effects on regional economic growth* (PhD thesis). Department of Economics, University of California – Davis.

Cappelen, A., Castellacci, F., Fagerberg, J., & Verspagen, B. (2003). The impact of EU regional support on growth and convergence in the European Union. *Journal of Common Market Studies*, *41*, 621–644. doi:10.1111/1468-5965.00438

Card, D., Jochen, K., & Weber, A. (2010). Active labour market policy evaluations: A meta-analysis. *Economic Journal*, *120*, F452–F477. doi:10.1111/j.1468-0297.2010.02387.x

Dall'Erba, S., Guillain, R., & Le Gallo, J. (2009). Impact of structural funds on regional growth: How to reconsider a 9 year-old black-box? *Région et Développement*, *30*, 77–99.

Dall'Erba, S., & Le Gallo, J. (2007). Cohesion policy, the convergence process and employment in the European Union. *Czech Journal of Economics and Finance*, *57*, 324–340.

Dall'Erba, S., & Le Gallo, J. (2008). Regional convergence and the impact of European structural funds over 1989–1999: A spatial econometric analysis. *Papers in Regional Science*, *87*, 219–244. doi:10.1111/j.1435-5957.2008.00184.x

De Dominicis, L., Florax, R. G. J. M., & De Groot, H. L. F. (2008). A meta-analysis on the relationship between income inequality and economic growth. *Scottish Journal of Political Economy*, *55*, 654–682. doi:10.1111/j.1467-9485.2008.00470.x

Dobson, S., Ramlogan, C., & Strobl, E. (2006). Why do rates of β-convergence differ? A meta-regression analysis. *Scottish Journal of Political Economy*, *53*, 153–173. doi:10.1111/j.1467-9485.2006.00374.x

Ederveen, S., De Groot, H. L. F., & Nahuis, R. (2006). Fertile soil for structural funds? A panel data analysis of the conditional effectiveness of European cohesion policy. *Kyklos*, *59*, 17–42. doi:10.1111/j.1467-6435.2006.00318.x

Ederveen, S., Gorter, J., De Mooij, R. A., & Nahuis, R. (2002). *Funds and games: The economics of European cohesion policy*. The Hague: CPB Netherlands Bureau for Economic Policy Analysis.

Egger, M., Davey Smith, G., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple graphical test. *British Medical Journal*, *315*, 629–634.

Esposti, R. (2007). Regional growth and policies in the European Union: Does the Common Agricultural Policy have a counter-treatment effect? *American Journal of Agricultural Economics*, *89*, 116–134. doi:10.1111/j.1467-8276.2007.00967.x

Esposti, R., & Bussoletti, S. (2008). Impact of Objective 1 funds on regional growth convergence in the European Union: A panel-data approach. *Regional Studies*, *42*, 159–173. doi:10.1080/00343400601142753

Fagerberg, J., & Verspagen, B. (1996). Heading for divergence? Regional growth in Europe reconsidered. *JCMS: Journal of Common Market Studies*, *34*, 431–448. doi:10.1111/j.1468-5965.1996.tb00580.x

Fujita, M., Krugman, P., & Venables, A. J. (1999). *The spatial economy: Cities, regions and international trade*. Cambridge, MA: MIT Press.

Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational Researcher*, *5*, 3–8. doi:10.3102/0013189X005010003

Goldstein, H. (2003). *Multilevel statistical models* (3rd Ed.). London: Edward Arnold.

Greene, W. H. (2012) *Econometric analysis* (7th Ed.). Upper Saddle River: Prentice Hall.

Jones, C. I. (1995a). Time series test of endogenous growth models. *Quarterly Journal of Economics*, *110*, 495–525. doi:10.2307/2118448

Jones, C. I. (1995b). R&D-based models of economic growth. *Journal of Political Economy*, *103*, 759–784. doi:10.1086/262002

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*, 483–499. doi:10.1086/261763

Le Gallo, J., Dall'Erba, S., & Guillain, R. (2011). The local versus global dilemma of the effects of structural funds. *Growth and Change*, *42*, 466–490. doi:10.1111/j.1468-2257.2011.00564.x

Mankiw, G. N., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, *107*, 407–437. doi:10.2307/2118477

Mohl, P., & Hagen, T. (2010). Do EU structural funds promote regional growth? New evidence from various panel data approaches. *Regional Science and Urban Economics*, *40*, 353–365. doi:10.1016/j.regsciurbeco.2010.03.005

Pellegrini, G., Terribile, F., Tarola, O., Muccigrosso, T., & Busillo, F. (2013). Measuring the effects of European regional policy on economic growth: A regression discontinuity approach. *Papers in Regional Science* 92, 217–233.

Puigcerver-Peñalver, M. (2007). The impact of structural funds policy on european regions' growth: A theoretical and empirical approach. *European Journal of Comparative Economics*, *4*, 179–208.

Ramajo, J., Márquez, M., Hewings, G. J. D., & Salinas, M. M. (2008). Spatial heterogeneity and interregional spillovers in the European Union: Do cohesion policies encourage convergence across regions? *European Economic Review*, 52551–52567.

Rodriguez-Pose, A., & Fratesi, U. (2004). Between development and social policies: The impact of European structural funds in Objective 1 regions. *Regional Studies*, *38*, 97–113. doi:10.1080/00343400310001632226

Rodriguez-Pose, A., & Novak, K. (2013). Learning processes and economic returns in European cohesion policy. *Investigaciones Regionales*, *25*, 7–26.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*, S71–S102. doi:10.1086/261725

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*, 65–94. doi:10.2307/1884513

Sutton, A. J., Abrams, K. R., Jones, D. R., Sheldon, T. A., & Song, F. (2000). *Methods for meta-analysis in medical research*. New York: Wiley.

Vickerman, R., Klaus, S., & Wegner, M. (1999). Accessibility and economic development in Europe. *Regional Studies*, *33*, 1–15. doi:10.1080/00343409950118878