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Carlos San Juan Mesonada (EconPol Europe, Universidad Carlos III Jean Monnet Chair and the UC3M Economics Institute) and Carlos Sunyer Manteiga (EconPol Europe, Universidad Carlos III de Madrid)

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Authors: Carlos San Juan Mesonada[1] and Carlos Sunyer Manteiga[2]

ABSTRACT

The paper attempts to recover empirical evidence related to the European Structural and Investment Funds (ESIF) to promote growth for the management of the Recovery & Resilience Facility (RRF). We analyse the impact of the EU Cohesion Policy on regional development over the period 1986-2018, using dynamic panel data models. In doing so, we use a neoclassical Solow growth model, extending the current literature in at least three ways. First, we make use of a new dataset, which contains highly detailed data on regional commitments and payments of Structural Funds; secondly, we address the endogeneity via a difference GMM estimator; finally, we control for the spatial interdependence among regions via a Spatial Durbin model. We find that the Cohesion Policy fosters regional growth both in the short and long run, regardless of the Objective considered. The role of the business cycle in the speed of regional convergence is quantified. The funds' effectiveness is hindered during the crisis, especially in the least developed regions, partly due to lower absorptive rates. Furthermore, human capital and quality of government are crucial growth determinants necessary for improving the performance of the Structural Funds. Finally, we discuss if the combination of ESIF & RRF funds will be appropriate for accelerating the post-pandemic recovery versus the financial recession recovery.

Key Words: Spatial panel econometrics, Generalised Method of Moments, European Union, Regional economic growth, Structural Funds.

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[1] Universidad Carlos III Jean Monnet Chair and the UC3M Economics Institute.
[2] Universidad Carlos III de Madrid.

1. INTRODUCTION

The European Union (EU) has a total budget of 1,082 billion euros for the programme 2014-2020. Approximately one-third of that budget corresponds to the European Structural and Investment Funds (ESIF), which consist of a set of financial instruments in the form of public transfers – managed by sub-national regions, termed NUT 2 according to Eurostat. The ESIF constitute the primary tool to promote the EU's social, economic and territorial cohesion, mainly for the least favoured regions (Treaty on the Functioning of the European Union, 2008).

In order to attain the convergence target, most of ESIF funds are allocated in those regions whose GDP pc measured in PPP is below 75% of the EU's average or those that, due to the statistical effect of the progressive enlargement of the EU, have a GDP pc slightly above that threshold. The former is known as Objective 1 or less developed regions (O1R) and the latter as "phasing-out" regions. The remaining funds are reserved for the other two objectives: Territorial Cooperation and Regional Competitiveness and Employment.

The NextGenerationEU (NGUE) programme will be an enlarged version of the Structural Funds to promote recovery and resilience after the pandemic recession. With €750 billion to boost the financial firepower of the EU budget, the NGUE funds will be raised on financial markets and not co-financed by the regions or the Member States (MS). The reinforced multiannual financial framework for 2021-2027 to channel investment is mainly based on the ESIF experience (European Commission, 2017). The NGUE includes: first, the Recovery and Resilience Facility (RRF), with 672.5 billion euros including grants and credits; and second, the REACT EU (€47.500 billion), an initiative that continues and extends the crisis response and crisis repair measures. Member States (MS) and regions will prepare recovery and resilience plans that set out a coherent package of reforms and public investment projects.

At this stage, and considering the size of these funds, it becomes crucial to evaluate ex-post the functioning of past ESIF and offer some experience-based suggestions for the design of the new programs. This paper focuses on assessing the convergence objective, measured as a reduction in the gap of GDP pc across regions, for the period 1989-2013 and the later recovery before the pandemic outbreak (2014-18), controlling by the business cycle phase.

With respect to this question, a common theoretical approach is, after discussing some of the pros and cons of the various econometric specifications employed in the literature, we make use of the neoclassical Solow growth framework. However, we focus greater attention on sources of potential bias, such as endogeneity, by using the Generalised Method of Moments, or the presence of spatial spillovers, allowing for spatial correlation in the individual shocks on the Dynamic Panel Data (DPD).

Among the papers based on the neoclassical growth framework, most of them either ignore the spatial dependence among regions (Esposti and Bussoletti, 2008) or use proxies to control for it (Rodríguez-Pose and Garcilazo, 2015). Only a few of them (e.g. Bouayad-Agha et al., 2013; Mohl and Hagen, 2010; 2011) rely on spatial econometric techniques mining to consider spatial and temporal dynamics in assessing the effects of ESIF. That is, they do not consider regions as isolated entities but interdependent ones, which seems more credible. Moreover, in this analysis, we estimate conditional-convergence econometric models using EU12 recently released high-quality data of a 28-year panel of 114 regions on ESIF's expenditures and appropriations. The extended sample (with data until 2018) and the number of regions considerably exceed the length of the period examined in previous research. And we also check the robustness of our results using data for EU28 (2000-18)

The added value of this paper is that difference between commitments and appropriations in DPD models. Additionally, our models include control variables for the impact on the convergence of the ESIF, in the different phases of the business cycle, using the public debt spreads. We also attempt to explain the long-term and short-term convergence rate differences using DPD models that allow for spatial correlation in the individual shocks.

Using appropriation data and Government Bonds Yields Spreads (GBYS) allows us to present new results about convergence along the bust and boost, covering the liquidity trap that hit the less developed regions in the periphery harder and highlighting the role of the business cycle in the absorptive capacity. The latter also allows us to consider the role of the economic situation in the absorptive capacity, previously only taken into account to a very small extent. Furthermore, the boost and bust are not treated as a dichotomic variable but as a continuous one, allowing the heterogeneity in the bust exposure of the different regions.

Short-run and long-run effects on the growth of the ESIF are also analysed. The long-term elasticity can be interpreted as showing that a one per cent increase of ESIF payments (as a per cent of GDP) raises the real GDP per capita by φ per cent. Furthermore, most of the previous studies do not discuss the long-term quantitative impact of ESIF payments, which can simply be calculated as $\varphi = (\beta_2/-\beta_1)$ in our models (Hagen & Mohl, 2011).

Following the concept of absorptive capacity, growth 'conditioning factors' such as spatial interconnections, human capital, population density, employment density and quality of the institutions, particularly, government effectiveness and the fight against corruption (Ketterer & Rodríguez-Pose, 2018; Rodríguez-Pose & Ketterer, 2020), are also taken into account in our models.

This paper is organised as follows: Section 2 reviews the related literature, followed by Section 3, where the data used is described. Then, Section 4 shows the econometric specification. The results are discussed in Section 5. Finally, some policy remarks and conclusions figure in Section 6.

2. LITERATURE REVIEW

There are mainly three strands of theories for the study of the role of public investments on economic growth. Based on Dynamic General Equilibrium Modelling, previous research on the assessment ex-ante always obtains a positive impact (e.g. Boscá et al., 2016). However, the literature focused on the assessment ex-post shows ambiguous results (for thorough reviews, see Dall'Erba and Fang, 2017; Pieńkowski and Berkowitz, 2016).

Another theoretical approach, synthetic controls, is to build up counterfactual scenarios to assess the impact of treated regions (O1R receiving ESIF) versus the non-treated regions scenario[3]. Cerqua and Pellegrini (2019) consider the Regression Discontinuity Designs, RDD, the non-experimental design closest to experimental design and one of the most credible evaluation strategies for estimating the causal impact of regional policies. Moreover, they highlight the main shortcomings: firstly, their results are local, so they cannot be extrapolated to the rest of the population as we aim to do in this study;

[3] A sample of developed regions "similar" in productive structure to the sample of O1R used as non-treated regions, labelled "counterfactual".

secondly, the design implies data grouped in programmes, so there is less variability, and the sample size is considerably shrunk.

Among the limits of GWR, multicollinearity may arise, which makes it more suitable for exploratory rather than confirmatory analyses. As an exploratory method, it measures the influence of the cohesion policy on growth more than the actual net impact, as can be done using a counterfactual method such as regression discontinuity design (Brunsdon et al. 1999; Fotheringham and Brunsdon, 1999).

On the other hand, Ali et al. (2007) questioned the interest and limitations of using geographically weighted regression (GWR). As they mentioned, the findings of GWR are more designed to be exploratory and to generate hypotheses than to test hypotheses. As Bourdin (2019) demonstrates, the spatial heterogeneity of growth must be completed by more in-depth investigations into the reasons for this heterogeneity.

We consider that the problem of the spatial heterogeneity is addressed for the case of neoclassical convergence models, like the one used in our analysis, in the theoretical aspects of controlling for spatial autocorrelation discussed in Ertur and Koch (2006) and López Bazo et al. (2004).

In our view, when dealing with datasets with spatial structure, it is very likely to find the presence of spatial interactions among the units studied, resulting in spatial heterogeneity and spatial autocorrelation. When this happens, it is advisable first to specify the spatial structure, then test if there are spatial effects and finally, if needed, include those effects in the models, and thus we did so.

The question of the spatial heterogeneity is addressed with a different methodology in our paper using panel data with GMM estimations instrumented with lags to avoid endogeneity and spatial autocorrelation bias, and includes control variables such as human capital, quality of institutions, and spillover effects.

Although a good deal of literature based on empirical evidence has focused on this topic, the results obtained differ widely. Differences in the research design, samples, period of study and quality of the data used are behind this lack of consensus. The heterogeneity of results is investigated, e.g., using a meta-analysis on econometric estimates of the ESIF impacts, pointing to three sources of differences: data characteristics, estimation methodology, and presence of regressors other than the ESIF (Dall'Erba and Fang, 2017). They highlight that the impacts on growth depend on 'conditioning factors' (Fratesi &

Wishlade, 2017), mainly on human capital, on the local quality of government (Becker, Egger, & Von Ehrlich, 2010; Accetturo, de Blasio, & Ricci, 2014; Rodríguez-Pose & Garcilazo, 2015; Ketterer & Rodríguez-Pose, 2018: Rodríguez-Pose & Ketterer 2020), on expenditure intensity (Cerqua & Pellegrini, 2018), on regional contextual conditions (Bachtrögler, Fratesi, & Perucca, 2019) or on the regional sectoral structure (Percoco, 2017).

Moreover, some papers emphasise the importance of institutions (Ederveen et al., 2006), the territorial capital (Fratesi and Perucca, 2014), or point out the importance of investment in R&D intensive industries (Midelfart-Knarvik and Overman, 2002).

While there is a line of research that concludes with a negative impact of the funds (Eggert et al., 2007), some studies find no impact (Boldrin and Canova, 2001; Le Gallo et al., 2011), a limited impact (Esposti and Bussoletti, 2008; Maynou et al., 2014) and others find evidence of a positive impact (e. g.: Becker et al., 2010; Pellegrini et al., 2013).

Somewhere in between, many studies condition the effectiveness of the funds by certain aspects. For example, Giua (2017) found a positive impact on employment and concentration of the effects in crucial sectors in Italian regions using RDD. However, the policy variable only refers to the eligibility of the municipalities and not to the effective expenditure amount. In fact, the use of eligibility is common in RDD applications on Regional Policy, although it certainly has some drawbacks (Becker et al., 2012; Giua, 2017).

Later on, Crescenzi and Giua (2020) find a positive impact of ESIF in some countries but not in others. De Dominicis (2014) finds it only in the less developed regions, and Rodríguez-Pose and Novak (2013) argue that the sign of the impact depends on the programme. Among the main reasons behind this divergence in the results, two can be highlighted in addition to the differences in the periods and samples of study: the quality of the data used and the research design. Thus, due to problems in data availability, many authors restrict their analysis to ESIF commitments (Esposti and Bussoletti, 2008) or simply use a dummy variable identifying whether the region is an O1R recipient (Becker et al., 2010) or simply receives support from the EU (Garcia-Milá and McGuire, 2001).

Furthermore, as Mohl and Hagen (2010) observe, at the beginning, studies were based on cross-sectional analysis (Rodríguez-Pose and Fratesi, 2004; Fratesi and Perucca, 2014). However, the panel data models gained popularity and Fratesi and Perucca (2019) estimated a panel data model, but used commitments because of their advantages (more variability, the possibility of getting rid of unobserved heterogeneity, less collinearity etc.), and nowadays, most of the analyses work with panel data.

Although the financing of the ESIF and the addition of a lagged dependent variable may potentially cause problems of endogeneity and simultaneity, as suggested by Abreu *et al*. (2005), recent studies have started addressing this issue either through the use of instrumental variables (Dall'erba and Le Gallo, 2008) or GMM (Mohl and Hagen, 2010)[4].

3. DATA AND DESCRIPTIVE STATISTICS

3.1 Data sources

The dataset consists of 174 NUTS2 regions corresponding to the EU-12 over a span of 25 years (1989-2013) and enlarged with the ARDECO last available data 1996-2018. Due to reasons of data availability, the German New Länder (except for the 2000-2018 sample), Ceuta, Melilla, Madeira, Azores and French overseas regions are excluded.

The data used for this research comes from several sources. First, with regard to the outcome variable of interest, that is, average annual growth of real GDP per capita in 2005 prices, data is collected from the Cambridge Econometrics' Regional Database at the NUTS2 (2013 classification) regional aggregation level.

Concerning the data related with the ESIF, in April of 2018, the European Commission (DG Regional Policy) released a dataset with annual regionalised data on both commitments and expenditures in current prices. That gives a significant advantage over many of the previous studies (e.g. Rodriguez-Pose and Fratesi, 2004; Esposti and Bussoletti, 2008), which were forced to work with either data on commitments or aggregated in programmes. As this data was in current prices, we deflate it using national GDP deflators (base 2005) available at the World Bank national accounts dataset.

[4] Other alternative designs recently used that also take into account this endogeneity issue are synthetic controls (Barone et al., 2016; Di Cataldo, 2017), generalised propensity score estimations (Becker et al., 2012) and Regression Discontinuity Designs (Becker et al., 2013; 2018; Giua, 2017; Pellegrini et al., 2013). However, these alternative designs also present certain shortcomings. See Cerqua and Pellegrini (2019) for an overview of the quantitative techniques for evaluating regional policies.

Whether or not a region is treated as Objective 1 (O1R), that is, if it receives the largest share of the funds, is inferred from documents of the European Commission[5].

Some of the control variables, such as population, employment and public investment, also come from the Cambridge Econometrics' Regional Database. Others, like educational attainment, expressed as the share of active population with only primary education (De la Fuente and Doménech, 2002), are obtained from Eurostat. Conversely, the index of government quality is constructed after combining data coming from two different sources: on the one hand, with cross-sectional data from the Quality of Government Institute of the University of Gothenburg, available at a regional level; on the other, with panel data from the World Bank´s World Governance Indicators database, available at a national level. Further details of the construction of this index can be found in Charron *et al.* (2014) and Rodríguez-Pose and Garcilazo (2015).

Apart from that, in some of the regressions we also control for the financial crisis. However, instead of doing it by simply including a dummy variable indicating when the crisis takes place, we follow Becker *et al*. (2018) and construct the government-bond-yield spreads (GBYS) with ten-year maturity. In this way, we manage to capture the differences in intensity across countries (the wider the spread, the harder the crisis hits). This variable is calculated by taking the difference between the harmonised long-term interest rates on government bonds and the short-term rates given by the ECB. Both rates can be found on the ECB´s website.

Finally, all the data containing geographical information needed for the construction of the spatial weight matrix comes from the Geographic Information System of the European Commission.

3.2 Descriptive statistics

This section provides the fundamental statistical differences in the critical variables of the O1R compared with non-O1R. First, Figure 1 presents the Kernel densities of ESIF expenditure pc by Objective 1 status and Figure 2 shows the evolution of GDP per capita

[5] For further details, consult Council Regulations 2052/88, 2082/93, 502/1999, 595/2006 and 189/2007

of treated and non-treated regions and laid the foundation for the hypothesis that the Financial Crisis represents a turning point in the trend to be investigated.

Second, we present the map that visually presents the hypothesis that there may be spillovers and show how the EU funds allocation is negatively correlated with regional income. **Table 1** shows some descriptive statistics of key variables pooled over the period 1989-2013 and 1996-2018 split by Objective 1 status. *GDP per capita* is measured in real euros; *ESIF expenditure* and *Total investment* in real euros per capita; *Employment/population density* in a number of workers/inhabitants per square kilometre; *Primary education* as the percentage of the active population with primary education; and *Quality of Government* is an index laying between 0 (lower quality) and 1 (higher quality).

Table 1a

Descriptive statistics NUTS2: 1989-2013

	Non Objective 1 regions				**Objective 1 regions**			
Statistics	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
GDP per capita	26845.08	7297.58	11214.37	70407.74	15419.18	3904.83	7690.89	35587.54
ESIF expenditure	31.79	51.89	0	778.6	240.95	165.42	3.13	1056.91
Total investment	5586.08	1714.13	1572.45	23754.3	3614.23	1395.09	1106.28	11917.45
Employment density	176.51	383.7	4.67	4282.57	60.39	106.73	5.63	680.17
Primary education	30.63	12.01	10.1	72	54.22	12.94	19	84.5
Population density	358.65	644.94	10.22	7228.89	154.82	261.93	10.37	1693.64
Quality of government QoG	0.75	0.12	0.16	1	0.53	0.21	0.16	0.9

Table 1b

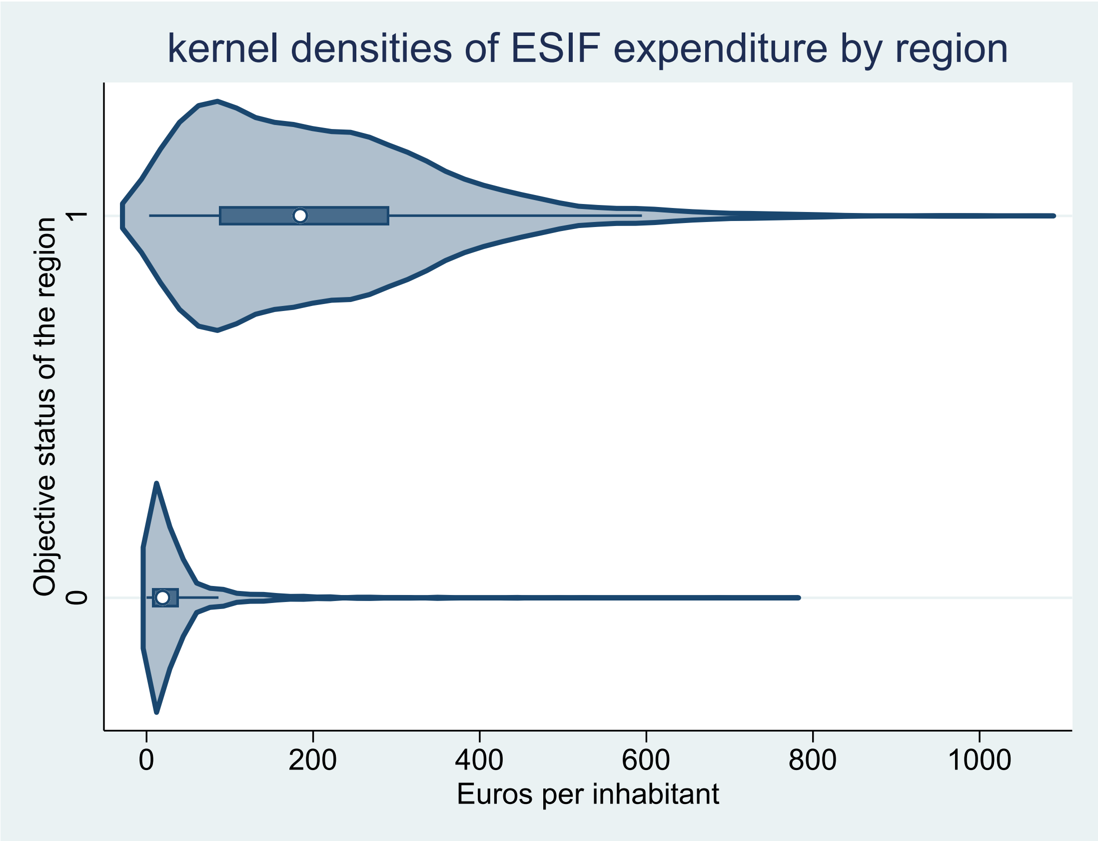
Descriptive statistics NUTS2: 1996-2018

	Non Objective 1 regions				**Objective 1 regions**			
Statistic	Mean	Std. Dev	Min.	Max.	Mean	Std. Dev	Min.	Max.
GDP per capita	27877.56	9566.60	5877.04	98640.10	15760.47	5479.95	5409.36	41705.11
ESIF expenditure	69.51	119.41	0	1061.65	298.89	233.85	4.08	1241.74
Total investment	5863.81	2306.63	1438.30	37758.94	3335.26	1197.60	1299.01	7991.78
Employment density	201.57	422.67	1.77	4351.41	46.13	42.96	2.78	172.38
Primary education	32.94	14.14	9.40	91.93	54.05	17.10	15.00	89.48
Population density	568.63	1320.19	10.42	11744.41	166.40	135.29	22.15	764.57

Source: Own elaboration with data from ARDECO and Eurostat Open data ESIF; QoG, broadly defined, such as corruption, impartiality, and quality of public services, from Gothenburg Institute of Quality of Government and World Bank. See Charron et al. (2014), Charron & Lapuente (2019) and directions from Rodríguez-Pose & Garcilazo (2015).

It is straightforward that regions non treated as Objective 1 present higher levels of income and investment, better regional governments and considerably higher employment and population densities. On the other hand, Objective 1 regions show a slightly lower level of educational attainment. In addition, and in line with the redistributive nature of ESIF, Objective 1 regions receive almost three times more funds than the rest of the regions (for the whole distribution, see **Figure 1**). Among other reasons, these differences are related to the productive structure. Thus, whereas Objective 1 recipients have 12% of the active population engaged in activities linked to agriculture, other regions barely have 3%.

Figure 1
Kernel densities of ESIF expenditure pc by Objective 1 status



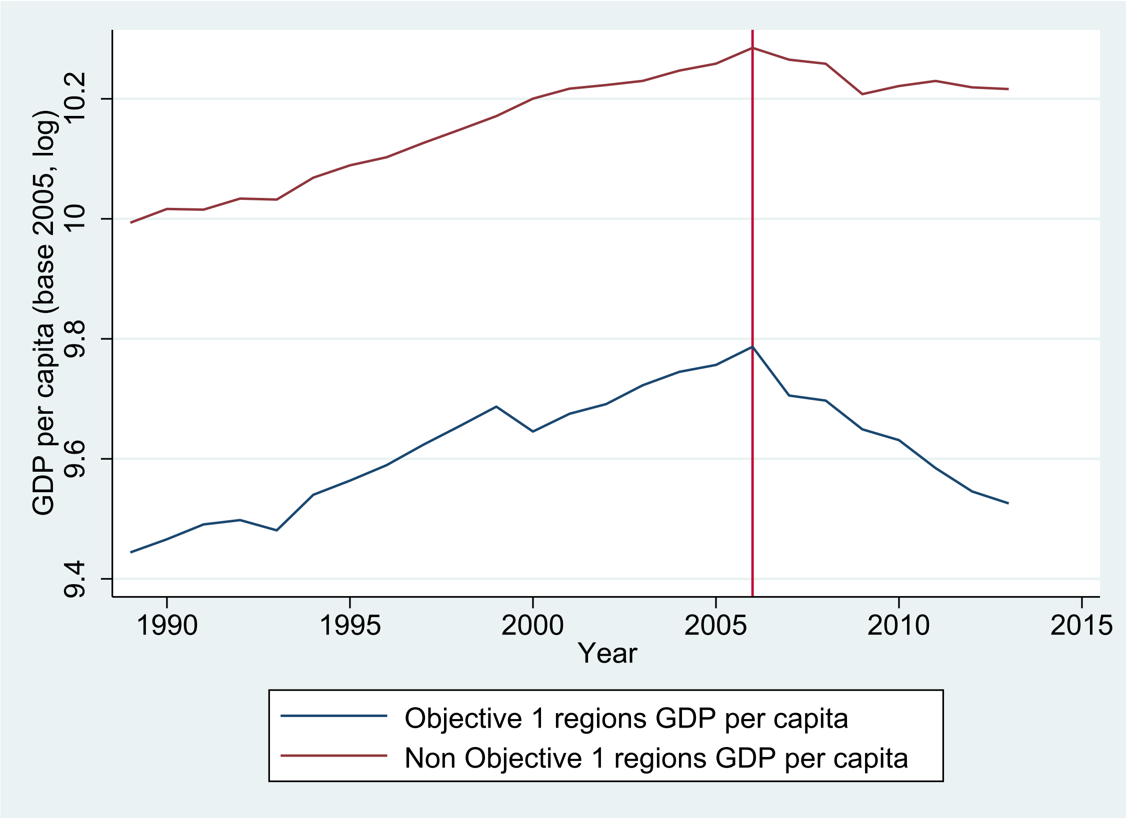
The following **Figure 2** graphically shows the evolution of GDP per capita of treated and non-treated regions over the period of study. From 1989 to 2006, the gap between personal incomes was gradually reduced, but from 2007 onwards, probably due to the financial crisis, this gap grew considerably, suggesting thus an asymmetric impact of the crisis on EU regions (Capello et al., 2015).

It seems reasonable to think that if one region grows, neighbouring regions will absorb part of this growth. That is, there are clubs of regions that converge at similar rates (as suggested in Dall'erba and Le Gallo (2008), where they differentiate between 'Core' and 'Periphery' regions) and later confirmed by Montañes et al, 2018[6] and Mazzola and Pizzuto, 2020[7] a. In **Figure A1,** this spatial interdependence is shown, as the least developed regions appear spatially concentrated. The maps also show how the EU funds allocation is negatively correlated with the regional income and how the EU enlargement has increased the relative income of some regions that in the past used to be below the 75% of the EU average income.

Figure 2
Annual income by treatment status.

[6] Montañés, et al (2018) found for Spain significant differences in the composition and behaviour of these clubs ex-ante and ex-post to the 2008 crisis. Rural provinces, especially the predominantly remote rural provinces, have had a better behaviour [in terms of growth during the bust] than urban and intermediate provinces. The degree of technological innovation and the urbanization of the province are the main determinants for explaining the creation of the clubs.

[7] Concerning the impact of the Great Recession on the convergence process for the EU-28, Mazzola and Piazzuto(2020 a) found evidence of two convergence clubs and provide evidence of the diverging impact of the Great Recession "between" the higher and the lower convergence clubs at both regional and country levels as well as of the strengthening of the convergence process "within" most clubs. At the ME level, the macroeconomic conditions may have played a key role. And they note that high levels of debt and deficit in proportion of GDP aggravated with the introduction of austerity packages may have strengthened the disparities. Sacristan and San Juan Mesonada, 2021 also found evidence of the policy-mix impact on convergence in the EU-28 during the boost and bust.



Note: The data refers to O1R included in each year.

4. EMPIRICAL FRAMEWORK

As mentioned above, we apply the neoclassical growth framework, in its simplest form, and then extend it with a dynamic panel specification and account for spatial spillovers. Hence, and in accordance with some recent growth literature (Bouayad-Agha *et al.*, 2013; Di Cataldo and Monastiriotis, 2018), this results in a conditional β-convergence model written as follows:

$$\ln(y_{i,t}) - \ln(y_{i,t-1}) = \beta_0 + \beta_1 \ln(y_{i,t-1}) + \beta_2 \ln(ESIF_{i,t}) + \beta_3 X_{i,t} + \varphi_i + \tau_t + \varepsilon_{i,t} \qquad (1)$$

where the subscripts i and t denote region and time, respectively. Regarding the variables used, $y_{i,t}$ is the real GDP per capita; $ESIF_{i,t}$ is our main variable of interest and indicates regional expenditure on ESIF funds per capita; and $X_{i,t}$ is a vector of regional characteristics, including population density, population growth, investments per capita, quality of institutions and human capital. The error structure is as follows: φ_i and τ_t are region-specific effects and time effects, respectively, while $\varepsilon_{i,t}$ is the i.i.d. residual term.

Under this framework, EU funding contributes to the growth rate if β_2 is positive and significant, and there is conditional β-convergence if β_1 is negative and statistically significant.

Note that $SF_{i,t}$ is expressed in per capita terms in order to avoid potential problems of simultaneity. Moreover, as some regions do not receive ESIF funding and $SF_{i,t}$ is a logged variable, we have added 1 to the amount of ESIF per capita, following, among others, Rodríguez-Pose and Garcilazo (2015). In some regressions, we have also included a dummy identifying the Objective 1 status to identify the impact of Objective 1 payments. It can be argued as well that certain ESIF payments might have an impact after a specific time. For that reason, up to two lags have been included in some of the regressions.

In the underlying conditional β-convergence model, regions are assumed to be independent and converge at the same speed. However, empirical evidence suggests the presence of regional interdependence due to, among others, migration and technological spillovers (Dall'Erba and Le Gallo, 2008). This interdependence has econometric implications, among which are the potential violation of the assumption of independent errors, which, if ignored, can lead to unreliable results. Hence, the model needs to be spatially augmented in order to capture these externalities. For that task, the specification of a weight matrix, W(k), containing connectivity information among regions is needed.

W(k) must be squared and contain 174 rows and columns, one for each region in the sample. Whereas the diagonal (w_{ii}) is composed of zeros, each w_{ij} represents the way region *i* and *j* are connected. Regarding the specification itself, we follow previous studies (Bouayad-Agha *et al*., 2013; Ertur and Koch, 2006; Mohl and Hagen, 2010) and choose a k-nearest neighbours' matrix with weights based on the geographical distance between centroids of the regions, which has the advantage of being strictly exogenous:

$$W(k) = \begin{cases} w_{ij}^*(k) = 0 & if\ i = j \\ w_{ij}^*(k) = 1 & if\ d_{ij} \leq d_i(k) \\ w_{ij}^*(k) = 0 & if\ d_{ij} \geq d_i(k) \end{cases} \quad (2)$$

Where w_{ij}^* is an element of W located in row *i* and column *j*, still unstandardised; d_{ij} is the distance between centroids of regions i and j; finally, $d_i(k)$ is the cut-off distance such that region *i* has exactly *k* neighbours. Above that distance, an absence of spillovers is assumed. In line with previous studies (Bouayad-Agha *et al*., 2013; Ertur and Koch, 2006; Mohl and Hagen, 2010), we set *k* = 10, but results do not vary significantly with k=5 and 15. In order to make the parameter estimates more interpretable, the matrix is row standardised, that is, the sum of all the elements in a row equals one. Thus, each weight corresponds to the total share that region has in the total spatial effect:

$$w_{ij}(k) = \frac{w_{ij}^*(k)}{\sum_j w_{ij}^*(k)} \tag{3}$$

It seems reasonable to use a k-nearest neighbours' weight matrix for this concrete sample as it allows every region to have the same number of neighbours, including islands. Otherwise, alternative specifications based not on arc distance, but on contiguity between regions, would leave the islands without weights. Moreover, using k-nearest neighbours reduces the spatial heterogeneity problem in the distribution of regions (Anselin, 2002).

Therefore, the final equation with spillovers effects is (4):

$$\ln(y_{i,t}) - \ln(y_{i,t-1}) = \beta_0 + \beta_1 \ln(y_{i,t-1}) + \beta_2 \ln(ESIF_{i,t}) + \beta_3 X_{i,t} + \beta_4 Wk + \varphi_i + \tau_t + \varepsilon_{i,t}$$

where Wk is the spatial matrix.

5. RESULTS

5.1 Panel regression results without spatial components

As the data we use in this analysis is not random, being subject to common shocks, we perform a modified Wald test for GroupWise heteroskedasticity. The results ($\chi^2(174)$=6170.57, p-value ≈0.00) lead us to reject the null hypothesis strongly, and thus robust standard errors are needed. We also reject the null hypothesis with the Breusch and Pagan Lagrangian multiplier test for random effects and the Hausman test, so the model should control for unobserved heterogeneity. Finally, further evidence of cross-sectional dependence (Pesaran's test) and first-order autocorrelation (Wooldridge and Baltagi–Wu tests), lead us to adjust the standard errors and employ a consistent covariance matrix like the one proposed by Driscoll and Kraay (1998). **Table 2** shows the results of these tests.

Table 2
Panel data state-specific effects tests

Wald test	
χ^2 -statistic	6170.57
p value	0.00
Cross-section random effects	
BPLM χ^2 -statistic	7.00

p value	0.004
Hausman test	
χ^2 -statistic	279.73
p value	0.00
Pesaran´s test	
χ^2 -statistic	202.58
p value	0.00
Wooldridge test	
F-statistic	259.89
p value	0.00

The results displayed in **Table 3** are in line with the predictions of the neoclassical growth framework. Regardless of the regression, past levels of GDP pc are negative and strongly significant, which gives evidence of conditional β-convergence. Furthermore, its size is similar to that obtained by Mohl and Hagen (2010) for the EU-15 and a shorter period of time (1995-2005).

Table 3
Regressions with Driscoll-Kraay standard errors

Dep. Var: GDP pc growth	(1)	(2)	(3)	(4)	(5)
Ln GDP pc (*t-1*)	-0.168***	-0.168***	-0.170***	-0.169***	-0.169***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)
Ln ESIF pc	0.002**	0.002**	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln investment pc	0.054***	0.053***	0.054***	0.054***	0.058***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ln employment density	0.028***	0.029***	0.026***	0.027***	0.039***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.006)
Ln population growth	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obj 1	0.014***				
	(0.003)				
Obj 1 x Ln ESIF pc		0.002***			
		(0.001)			
Ln ESIF pc (*t-1*)				-0.001	0.000
				(0.001)	(0.001)
Ln ESIF pc (*t-2*)					0.001
					(0.001)
ESIF long-term elast. (size)	0.012**	0.013**	0.019***	0.018***	0.018**
long-term elast. (*p-value*)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
No. of observations	4,175	4,175	4,175	4,175	4,002
R-squared	0.423	0.422	0.418	0.418	0.418
No. of regions	174	174	174	174	174

Regarding our key variable of interest, that is, ESIF *per capita* (β_2), although of a small size, it is significant and positive in all the regressions. Moreover, when we include a dummy indicating the Objective 1 status (1 if treated, 0 otherwise), the size of the coefficient increases (Column (1)). However, when we cross that dummy with the ESIF variable, the coefficient is equal to β_2 (Column (2)). This leads us to think that the difference between the dummy (0.014) and the ESIF (0.002) coefficients obtained in the first column is due not to a different impact of the ESIF on the poorest regions, but to other reasons. As it could be argued that EU funds become effective only after a certain time, in the remaining columns, we add one and two lags to the ESIF variable (columns (4) and (5), respectively). However, neither coefficients are significant. Finally, as the specification is dynamic, we can also derive from the regressions the long-term elasticity (θ) of ESIF[8]. This coefficient is again positive, significant and similar across the five regressions. In column (1), for instance, an increase of 1% in ESIF per capita raises the personal regional income in the long-term by 0.012%, which makes it quite comparable to the 0.016% found by Becker *et al.* (2010).

Eventually, the signs in the coefficients of the remaining variables are the expected ones. Hence, whereas population growth is negative, higher employment density and, above all, higher rates of investment pc, seem to spur the economy.

As discussed above, estimations in **Table 4** may be biased due to the endogeneity of the regressors. Hence, we re-estimate the model again, but using a two-step difference GMM estimator (Arellano and Bond, 1991). All variables are considered endogenous and the standard errors are finite-sample corrected (Windmeijer, 2005). Moreover, and in order to keep the properties of the Hansen test (Roodman, 2009) and avoid problems of overfitting instrumented variables (Bowsher, 2002) the number of lags is limited to four.

Note that the two-step system GMM proposed by Blundell and Bond (1998) is discarded since the panel is balanced, β_1 is far from being a unit root ($\beta_1 \to 1$) and the GMM estimates obtained lie above the Within Groups estimates (for more details of this rule of thumb, see Bond *et al.,* 2001). Hence, little or no gains in efficiency can be obtained from using a system GMM estimator, with the added problem of introducing more instruments.

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Derived as follows:

$$\ln(y_{i,t}) = \beta_1 \ln(y_{i,t-1}) + \beta_2 \ln(ESIF_{i,t}) \leftrightarrow \ln(y_{i,t}) - \ln(y_{i,t-1}) = (\beta_1 - 1)\ln(y_{i,t-1}) + \beta_2 \ln(ESIF_{i,t})$$
$$\leftrightarrow \ln(y_{i,t}) - \ln(y_{i,t-1}) = \alpha \ln(y_{i,t-1}) + \beta_2 \ln(ESIF_{i,t}) \leftrightarrow \ \theta = \beta_2/-\alpha$$

Given this specification, results in **Table 4** fail to reject the null hypothesis of the second-order serial correlation test proposed by Arellano and Bond (1991), leading us to validate the moment restriction for the autoregressive term. In addition, the Hansen test is not significant either. Consequently, there is no evidence of correlation between the instruments and the residuals. Nevertheless, since most of the *p-values* obtained from this test are above 0.6, these results should be treated with scepticism (Roodman, 2009).

Regarding the coefficients obtained, they are in line with the results shown in **Table 5**, being slightly higher for the case of our variable of interest. The results imply that increasing the payments of ESIF funds by 1% leads to an increase of 0.004% in the regional GDP per capita in the short run and around 0.04% in the long run. In contrast with **Table** 4, now the coefficients for the Obj 1 variables (columns (1) and (2)) are higher and significant, which indicate that funds allocated in the least developed regions are more effective.

Table 4
GMM-DIFF regressions

Dep. Var: GDP pc growth	(1)	(2)	(3)	(4)	(5)
Ln GDP pc (*t-1*), β_1	-0.170**	-0.154**	-0.197***	-0.203***	-0.218***
	(0.069)	(0.066)	(0.075)	(0.050)	(0.049)
Ln ESIF pc, β_2	0.004*	0.005**	0.005***	0.005***	0.004**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Ln investment pc	0.071***	0.069***	0.087***	0.073***	0.071***
	(0.016)	(0.016)	(0.019)	(0.014)	(0.014)
Ln employment density	0.118**	0.119**	0.101*	0.127***	0.142***
	(0.059)	(0.057)	(0.060)	(0.045)	(0.044)
Ln population growth	-0.211	-0.291	-0.158	-0.447**	-0.435*
	(0.303)	(0.294)	(0.334)	(0.219)	(0.225)
Obj 1	0.037***				
	(0.010)				
Obj 1 x Ln ESIF pc		0.007***			
		(0.002)			
Ln ESIF pc (*t-1*)				0.004**	0.004**
				(0.002)	(0.002)
Ln ESIF pc (*t-2*)					-0.001
					(0.001)
ESIF long-term elast. (size) ϕ	0.025	0.033	0.042**	0.044***	0.037***
long-term elast. (*p-value*)	(0.017)	(0.021)	(0.027)	(0.013)	(0.011)
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000
AR(2) (p-value)	0.179	0.498	0.106	0.798	0.197
Hansen (p-value)	0.855	0.932	0.910	0.984	0.964
No. of instruments	131	131	109	233	252

No. of observations	4,001	4,001	4,001	4,001	3,828
No. of regions	174	174	174	174	174

5.2 Panel regression results with spatial components

So far, the only spatial consideration we have adopted in our analysis is the standard errors correction proposed by Discoll and Kraay (1998). Yet it is clear that in our sample of 174 regions, where most of them share a border with at least one region, there is spatial interdependence (see in **Figure A2** and **Figure A3** Moran's I scatterplot for the ESIF and growth variables, respectively). Hence, we address this issue by extending our model with the spatial weight matrix described in Section 4.

In this context, two possible types of specifications arise: either to include a spatially weighted variable/s or a spatially weighted error term. We select the model following the strategy described in Belotti *et al.* (2017) and Elhorst *et al.* (2010). Thus, we start estimating a Spatial Durbin Model (SDM) with both dependent and independent variables spatially weighted (the general form would be $y_{i,t} = \rho W y_{i,t} + \phi W X_{i,t} + \varphi_i + \tau_t + \varepsilon_{i,t}$ where W represents the spatial weight matrix) and then test whether ϕ=0 (Spatial ϕ Autoregressive Model) or ϕ = -βρ (Spatial Error Model). Since we reject both tests at a 99% confidence level, the model chosen is SDM.

Unfortunately, we are unable to address the endogeneity and spatial dependence problems simultaneously. This is due to the fact that while GMM estimators assume an absence of Jacobian term involved in the procedure, by including a spatial weight matrix in the model, we inevitably generate a non-zero log-Jacobian transformation from the disturbances to the dependent variable. Hence, we cannot exactly state what the impact of the ESIF is on the economy, but suggest within which boundaries such impact lies.

Table 5
Spatial regressions

Dep. Var: GDP pc growth	(1)	(2)	(3)	(4)	(5)
Ln GDP pc (*t-1*), β_1	-0.121***	-0.121***	-0.122***	-0.124***	-0.124***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ln ESIF pc, β_2	0.002***	0.003***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln investment pc	0.017**	0.017**	0.018**	0.019**	0.019**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ln employment density	0.069***	0.070***	0.064***	0.065***	0.065***
	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)
Ln population growth	-0.766***	-0.761***	-0.729***	-0.724***	-0.719***

	(0.138)	(0.139)	(0.142)	(0.142)	(0.141)
Obj 1	0.017***				
	(0.004)				
Obj 1 x Ln ESIF pc		0.003***			
		(0.001)			
Ln ESIF pc (*t-1*)				0.001	-0.000
				(0.001)	(0.001)
Ln ESIF pc (*t-2*)					0.001
					(0.000)
ESIF long-term elast. (size) ϕ	0 .020**	0.021**	0.032***	0.032***	0.030***
long-term elast. (*p-value*)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
ρ	0.534***	0.531***	0.552***	0.545***	0.539***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.019)
No. of observations	4,002	4,002	4,002	4,002	4,002
No. of regions	174	174	174	174	174

The results of the spatial regressions are reported in **Table 5**. These are again in the same direction of the previous sets of regressions, that is, ESIF funds do spur economic growth and there is evidence of β-convergence among EU-12 regions. However, the coefficients obtained lie between the GMM (upper bound) and Discoll and Kraay (lower bound) estimations. Thereby, in the short run, while **Table 4** reveals a β_2 of a size between 0.004-0.005, **Table 3** and **Table 5** estimate an impact in the 0.002-0.004 range[9]. At the same time, in the long run, the Driscoll-Kraay approach suggests an impact of 0.01-0.02, the spatial regressions estimate it around 0.02-0.03 and GMM between 0.03 and 0.04. Something similar occurs with the coefficients of the variables that attempt to capture differences in the behaviour of Objective 1 recipients and the rest of the regions. This decrease in the effect concerning the GMM results might be because previously we were attributing to regions some part of the neighbouring regions' impact. This spillover measure is now captured in **Table 5** by ρ and implies that an increase of 1% in the ten nearest neighbours' personal income leads to a rise of around 0.54% in the economic growth of region i. This finding is in line with the literature (Dall'erba and Le Gallo, 2008; Mohl and Hagen, 2010).

In **Table 6,** we further extend our analysis in four ways: by adding human capital, quality of government, controlling for the last financial crisis and, finally, by looking into the **absorption rate of EU transfers**. Since some of these additional variables are only

[9] The β ranges between 0.001 and 0.007 enlarging the sample until 2018 with Driscoll-Kraay and from 0.002 to 0.006 estimating with two steps GMM (1996-2018) Tello & San Juan Mesonada, 2021 Mimeo.

available from 2000 onwards, we limit our analysis for the period **2000-2013**. Likewise, note that for reasons of data availability not all the regions (174) are included in the regressions.

In Columns (1) and (2) both human capital (primary education) and quality of government (QoG) have the expected sign. Government quality stands out as a great driver of economic growth, being highly significant and with a coefficient considerably larger than other traditional variables used in the related literature (e.g. employment density). As QoG is inversely and highly correlated (-0.592) with the amount of ESIF spent, the latter loses significance when both are included in the regression (Column 2)[10]. However, the QoG coefficient is robust to the exclusion of the ESIF variable. In addition, one could argue that QoG is endogenous (Acemoglu *et al.,* 2001). Hence, we also run GMM estimations obtaining no significant differences in the coefficient obtained (results available upon request). For further details, see in **Figure A4** the regional distribution of this variable.

Regarding the financial crisis (Columns (3) and (4)), the GBYS coefficient implies that an increase of one unit in the spread leads to a decrease in the growth rate of 0.6% (2000-2013), meaning 0.3 points over the average before the financial crisis (1996-2007). Moreover, its impact on Objective 1 regions is around twice that in other regions, thus giving a possible explanation for the divergence observed after 2007 (**Figure 2)**.

Table 6
Spatial regressions (2000-2013)

Dep. Var: GDP pc growth	(1)	(2)	(3)	(4)	(5)	(6)
Ln GDP pc (*t-1*)	-0.163***	-0.246***	-0.209***	-0.209***	-0.159***	-0.205***
	(0.023)	(0.025)	(0.021)	(0.021)	(0.023)	(0.020)
Ln ESIF pc	0.006***	-0.001	0.006***	0.006***	0.007***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln investment pc	0.035***	0.024***	0.010	0.010	0.035***	0.012
	(0.010)	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)
Ln employ. density	0.145***	0.150***	0.081***	0.082***	0.141***	0.068***
	(0.034)	(0.030)	(0.027)	(0.027)	(0.033)	(0.026)
Ln popul. growth	-0.643***	-0.222	-0.592***	-0.603***	-0.616***	-0.638***
	(0.205)	(0.214)	(0.177)	(0.182)	(0.207)	(0.170)
Primary education	-0.024*	-0.024*				
	(0.014)	(0.013)				
QoG		0.415***				

[10] However, enlarging the sample until 2018 we obtain a β = 0.007 and QoG = 0.071, both at 1 percent significance (Tello & San Juan, 2021). Possibly, the latter indicates that during the financial recession and later recovery the quality of government has been crucial for convergence.

		(0.048)				
GBYS			-0.006***	-0.005***		
			(0.001)	(0.001)		
Obj 1				0.013***		
				(0.004)		
Obj1xGBYS				-0.011***		
				(0.001)		
Diff					-0.078***	-0.051**
					(0.021)	(0.021)
DiffxGBYS						-0.091***
						(0.005)
spillover ρ	0.500***	0.528***	0.529***	0.524***	0.470***	0.491***
	(0.034)	(0.030)	(0.031)	(0.032)	(0.036)	(0.034)
No. of observations	1,918	1,918	1,918	1,918	1,918	1,918
No. of regions	137	137	137	137	137	137

Finally, in Columns (5) and (6), as mentioned above, we study if there is any impact on growth when regions do not spend all the funds expected for a certain year (the so-called absorption rate). To the best of our knowledge, only Becker *et al.* (2018) have considered this issue, finding that “regions with a higher crisis exposure also had a lower absorption rate during 2007-13, as it is indicated by a correlation coefficient of -0.504 between the two measures”. We extend that insight by constructing a variable that measures yearly the difference between funds budgeted and funds spent (variable Diff). Not surprisingly, we find that this gap has a negative impact on growth and becomes worse during downturns. One possible explanation is that during financial crises, when regional governments see their public budgets reduced, due to the additionality principle, the situation worsens by not being able to use the transfers received for not complying with the minimum co-financing rate required. Although the EU addressed this issue in 2011 by reducing the necessary co-financing rates (EU Council Regulation 18512/11), it seems that this measure came too late.

6. DISCUSSION

In contrast with other studies (e.g. Mohl and Hagen, 2010), our results show that European transfers foster regional development, regardless of the Objective analysed. This difference might be due to the structure of the dataset used, which until very recently (the dataset used in this study was published for first time in April 2018) were incomplete. This positive impact of the funds is significant both in short and in the long run, finding for the latter that an increase of 1% in the EU aid, leads to permanent increases of personal income calculated around 0.03%-0.04%. Thereby, by increasing the GDP per capita of the recipient regions, the cohesion policy counterbalances to some extent the increasing concentration of income in the wealthiest regions predicted by the New Economic Geography.

Furthermore, our analysis suggests that funds allocated in Objective 1 regions, despite being substantially more abundant, are no more effective than those granted to other regions are. The latter might be due to their lower absorption capacity, as they lack specific factors that have been proven essential for economic growth, such as human capital and institutional quality. For this reason, strengthening the independent ex-post monitoring of the objectives reached by the funds in these regions, as established in the current NextGenerationEU, could increase their effectiveness. The latter would require greater cooperation between the European Commission, MS and regional governments, as well as more thorough evaluations of the investments made. This need for a better evaluation culture has also been recently emphasised by the Commission (European Commission, 2019).

This paper also sheds light on the pernicious effect of the last financial crisis in the functioning of the Structural Funds. The least developed regions were the most hard-hit after the downturn, and this reversed the β-convergence observed over the period. At the same time, the effectiveness of the funds was lower in those regions deeply impacted by the recession. We found that the latter is partially due to lower absorption rates observed in the Objective 1 regions that could not spend all the money budgeted because of the additionality principle. Two alternative solutions arise. First, the one already considered by the EU consists of relaxing this principle, at least during downturns; secondly, to adapt the funds according to the business cycle phase. In this way, designing an anti-crisis fund could help escape the liquidity traps. This expansive perspective is shared, among others, by Blanchard *et al.* (2017), who emphasise that the funds are more effective for promoting growth during recessions and more effective in the peripheral region under a liquidity trap than in the centre. We expect that the NextGenerationsEU may cover this recovery function.

Regarding the limitations of our study, one could argue that controlling for endogeneity and spatial correlation in separated regressions gives a partial picture of the fund's effectiveness. However, to the best of our knowledge, so far no econometric techniques have been developed to combine GMM and spatial procedures. Therefore, in the absence of proper instruments, we are limited to providing ranges within which lies the effect of the funds. Moreover, since our estimations are based on annual data, one could argue that this makes our results misleading. Indeed, some studies have sorted out this problem by using 5-year averages (e.g. Becker *et al.,* 2018; Bouayad-Agha *et al*., 2013). However, in this study, we have given more priority to the asymptotic robustness of our results, needing for that purpose to work with yearly observations. Differences in the convergence rates and the impact of the funds could shed light on what policies should be taken/discarded. In particular, enlarging the sample to the post-financial boost, we found that the convergence rates fall 2 % during the bust (from -0.319 to -0.111 between 1996-2007 and 2008-2018).

Part of the available literature does not distinguish between long-run and short-run impact on the growth of the ESIF (Table 4) that could be quite different depending on the period and the phase of the business cycle (Mohle and Hagen, 2010; 2011; San Juan Mesonada and Sunyer Manteiga, 2020). The GBYS significance indicates it is relevant. Mainly in the busts, large spreads may signal liquidity trap situations.

To check the robustness of our estimates, we enlarge the sample until the last available data (2018) in Table 7. Comparing the results with the GMM estimation of the model before and after the crisis shows the same regularities as mentioned before, independent of the period. The short-run impact of ESIF on growth estimates are significant, and actually smaller than in the long run[11]. The Regional convergence is decelerating during the bust and accelerating during the boost. The quality of government, QoG, is very relevant to the absorption capacity at any time. The Government Bond Yield Spreads, GBYS, capture bust impact exposure and always have a negative coefficient as expected, meaning that the lower the spread, the higher the growth elasticity. Cross-effects significance of the Obj1xGBYS indicates that O1R used to be more growth-elastic during the busts. As expected, regions that concentrate human capital with only primary education tend to be less growth-elastic. Finally, the region's population rate is significant,

[11] We also test for the EU28 period 1986-2018, and our estimates show that the β ranges between 0.008 and 0.006 for the EU15 older MS's. The ESIF long-run elasticity on growth ϕ (between 0.03 and 0.04) is significant and clearly over the short run β elasticity (around 0.001 to 0.006). For 1996-2018 ϕ is 0.014 using GMM but increases to 0.028 using Driscoll-Kraay robust standard errors (Romero and San Juan Mesonada, 2021. Table 1).

explaining growth (as well as the employment density) that could be pointing to a breach of effects between rural and urban areas within the region.

Table 7a
GMM System Two-Step estimation by periods, UE-12

Dep. Var GDPpc	1996-2007	2008-2018
Ln GDP pc (*t-1*)	-0,319***	-0,111***
	(0,051)	(0,021)
Ln ESIF pc	0,002***	0,001**
	(0,001)	(0,001)
Ln pub expend pc	0,066***	0,149***
	(0,008)	(0,023)
Ln Employment density	0,054	0,135***
	(0,073)	(0,042)
Ln Population Growth	-0,171**	-0,063***
	(0,069)	(0,015)
Educat Level	-0,002***	-0,001***
	(0,001)	(0,001)
QoG	0,049***	0,053***
	(0,015)	(0,015)
GBYS	-0,003**	-0,002**
	(0,001)	(0,001)
Observations Nº	1.530	1.575
AR(1)	0	0
AR(2)	0,077	0,081
Hansen (p-valor)	0,412	0,885
Number of regions	175	175

Table 7b
GMM System Two-Step estimation (1996-2018), UE12

Dep. Var GDPpc	(1)	(2)	(3)
Ln GDP pc (*t-1*)	-0,411***	-0,411***	-0,417***
	(0,036)	(0,036)	(0,036)
Ln ESIF pc	0,002**	0,005**	0,006**
	(0,001)	(0,002)	(0,002)
Ln pub expend pc	0,139***	0,138***	0,136***
	(0,018)	(0,018)	(0,018)
Ln Employment density	0,022	0,019	0,016
	(0,040)	(0,042)	(0,045)
Ln Population Growth	-0,113*	-0,119**	-0,117*

	(0,047)	(0,046)	(0,047)
Educat Level	-0,004***	-0,004***	-0,004***
	(0,001)	(0,001)	(0,001)
QoG	0,049***	0,053***	0,054***
	(0,015)	(0,015)	(0,014)
GBYS	-0,002*	-0.002**	-0,002**
	(0,001)	(0,001)	(0,001)
Ln ESIF pc (*t-1*)		-0,007	-0,003
		(0,009)	(0,002)
Ln ESIF pc (*t-2*)			-0,009
			(0,009)
Observations Nº	3.500	3.500	3.325
AR(1)	0	0	0
AR(2)	0,234	0,117	0,152
Hansen (p-valor)	0,951	0,885	0,991
Number of regions	175	175	175

Note: ***, **, * denote significant level at 1, 5, y 10 per cent, respectively. Standard errors in parenthesis as usual.

Source: Tello and San Juan Mesonada, 2021, T-3 and T-4.

Our results, for the UE-28 comparing Western versus Eastern MS using a DPD model including data from 2000-2018, extend the analysis to 288 regions and compare NUT2 results between old EU-15 and new EU-12 exploring the convergence differences within the EU-28. During 2000-2018, the β-convergence rate is higher at the EU-28 level than the one obtained in previous studies, with a convergence at an annual rate of 13.5% and 16%. Additionally, each percentage point of country public debt spread decreases the rate of growth by 0.003% (Sacristan and San Juan Mesonada, 2021). Our empirical estimates for the UE-28 (including Norway and the UK) indicate that convergence speed is higher in the Eastern regions than in the Western ones (between 0.06 and 0.08 using FE and Discroll-Kray error and between 0.04 and 0.08 using GMM System Two-Step estimation). We control for spillovers; moreover, the coefficients for spillovers is not significant at p<0.1% and at p<0.05 is around 0.003 in the FE and Driscoll-Kray error and between 0.01 and 0.08 using GMM.

7. Policy Implications

The results of the ex-post evaluation of the impact of the ESIF profoundly depends on the extent of the sample (number of O1R included) and the length of the years of the study.

The business cycle affects the speed of convergence of the regions. In general, it is faster during the boost versus the bust, even finding divergence in certain countries (e.g., see for the EU-28 Mazzola and Pizzuto, 2020a and 2020b and for Spain, Montañes et al., Olmos and Reyes, 2018; San Juan Mesonada and Sunyer Manteiga, 2020). The fiscal deficit affects the absorption capacity of the O1R negatively during the bust due to the principle of complementarity and the requirement of co-financing the ESIF projects. However, the Commission acknowledged that, during the post-2008 bust, some of the O1R were in a liquidity trap and the co-financial requirements were eased, but maybe too late (Sacristan and San Juan, 2021 and Mazzola and Pizzuto, 2020 a).

8. Lessons for the *NextGenerationEU* implementation from the ex-post evaluation of the impact of the cohesion policy

The Commission has been trying to incorporate academic results into policy design. Furthermore, that effort also percolates in the design of the NGEU fund for recovery and resilience after the pandemic COVID19 recession.

Research into the ex-post evaluation of the impact of the cohesion policy has expanded in recent years, supporting the relevance of absorbing capacity of the regions for the effectiveness of the structural policy. The latter is coherent with our results and may be crucial for the implementation of the NGEU. Moreover, the intensity of the treatment matters and NGEU accounts for €750 billion versus only €200 billion for the ERDF 2014-20. For the first time in history, the agreement that the EU finance the NGEU with Eurobonds is also a relevant difference with the co-financed ESIF. This could push the recovery, keeping markets from discriminating against some MS through public debt spreads.

An additional warning, also for the practical implementation of the NGEU, came from the Das et al. (2020) paper on the leading players in the R&D expenditure per head impact on income, which found that R&D expenditure and per capita GDP growth rates have long-run associations for high-income and upper-middle-income groups. Hence, the study prescribes that excessive spending in R&D at the cost of other sectors needs to be reviewed[12]. The continuous evaluation of the NGEU projects results in the *Economic Semester* may be a way to solve these issues, even though it will be complicated to distinguish between the ESIF and the NGEU effects on growth.

A highly relevant area where ME's public sector competence may affect growth is public procurement since the country's spending power has enormous potential to affect socio-economic change (Marques & Morgan, 2018). Furthermore, the more significant elasticity to the growth of the public demand during recessions will amplify the long-run regional convergence's ESIF impact[13]. Finally, an expansive policy mix also plays its role in avoiding liquidity traps (Romero and San Juan Mesonada, 2021).

9. CONCLUSIONS

This paper aims to assess the effects of the Structural Funds in European regional convergence. For this purpose, we use a new database released by the European Commission that includes both annual commitments and payments allocated regionally over the period 1989-2013, thus allowing us to cover four programming periods. Furthermore, for a robustness check, we enlarge the sample until 2018 and test including EU28 (220 NUT2 for 2001-18) finding that the main results hold. Moreover, the convergence rates in the new Member States are much faster than in the old ones.

Our convergence rates results show relevant differences in the short and long term impact of the ESIF and explain the different results in previous literature that mainly focus on short term using budgeted funds instead of actual appropriations. Empirical results also clearly show that avoiding liquidity traps in less developed or peripheral regions is relevant and that the business cycle phase is critical for convergence.

Using a dynamic panel data approach, we consider, among other issues, the role of spatial interdependence. We find empirical evidence that spatial interconnectivity plays a vital role in regional development, which implies that programmes aimed at stimulating regional spillovers, such as *Interregional* or investments in infrastructure, are especially

[12] Unfortunately, data and empirical tests are scarce (Gianelle, 2019) and "the practical returns in terms of additional local economic impacts of the 'place-based approach' introduced on the basis of the recommendations of the Barca Report (Barca, 2009) are still hard to evaluate" (Crescenzi & Giua, 2020, p. 10).

[13] However, the Brekke (2020) policy implication results suggest that it is critical to improving regional design innovation and higher education policies so that entrepreneurial discovery process (EDP) processes can strengthen universities' entrepreneurial system-level role in core and peripheral areas.

beneficial in the long run since their impact is twofold. On the one hand, they foster regional growth directly, and on the other hand, do it indirectly through other channels, such as the economic influence of neighbouring regions.

The state-of-the-art regional development theories highlight the critical role of social capital translated in our synthetic index of quality of government, QoG (Charron et al., 2019; McCann and Ortega-Argilés 2014; Capelo et al., 2015). The stark contrast between the latter and the under-developed democratic institutions in some Objective 1 regions, which, together with risk-averse mentality, limits experimentation and flexibility in decision-making stunt growth. A potential solution to this problem lies in improving multi-level coordination, which would allow structural policies to draw on local knowledge and strengths (place-based agenda) while benefiting from the MS's capacity that often only exists at higher MS government levels. It would also create regional cross-learning opportunities while respecting the idiosyncratic regional institutions.

Summing up, the significance of our variables quality of government and spillovers are backed by the available literature about *smart strategy*. Admittedly, our results are only an empirical ex-post evaluation of the impact on the regional convergence of the ESIF. However, they may apply to the NextGeneratonEU funds' effectiveness, reinforcing the relevance of our finding that convergence accelerates during expansions while it shifts to low rates of convergence or even divergence during recessions. Dynamic and quick implementation of the recovery projects financed by the NextGenerationEU programmes will be critical for a rapid European recovery, reinforcing the convergence forces from the structural fund's incentives to growth and quality employment of the less developed regions.

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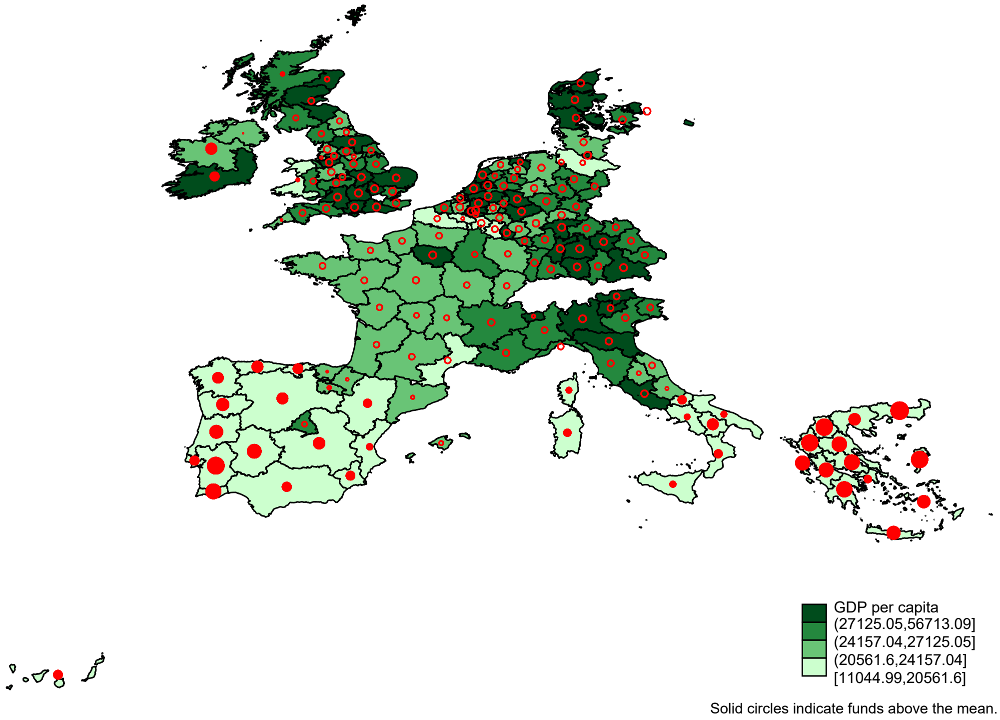
APPENDIX

Figure A1
Geographic distribution of GDP pc and EU funding for the periods 1989-1993 and 2007-2013



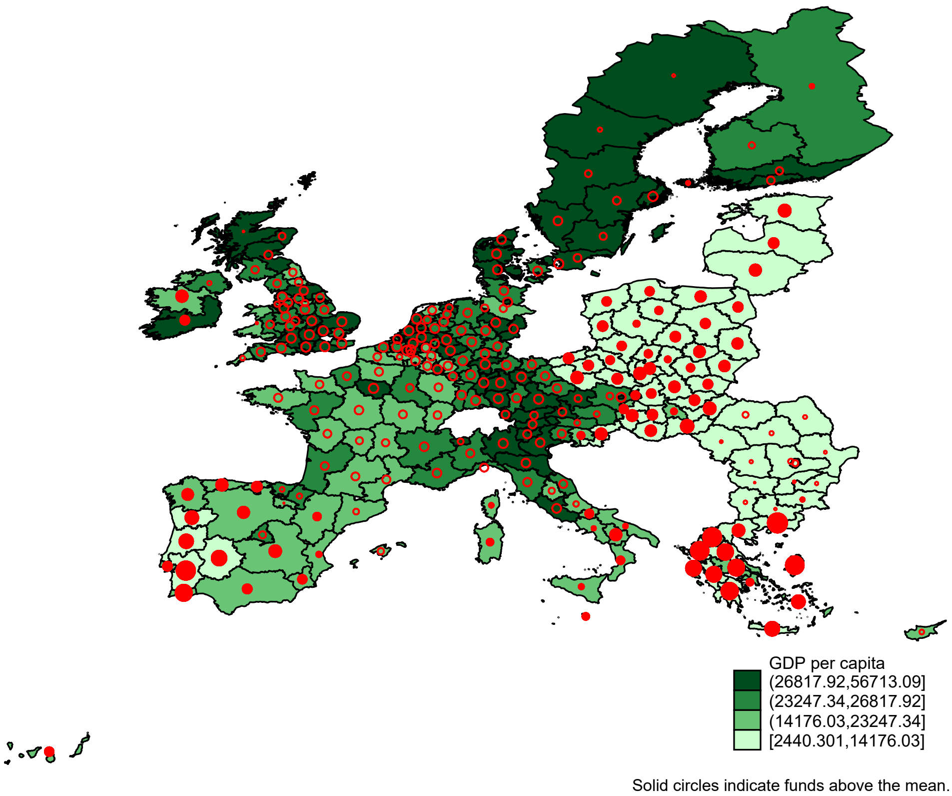


Figure A2
Moran´s I statistic test for the variable of interest

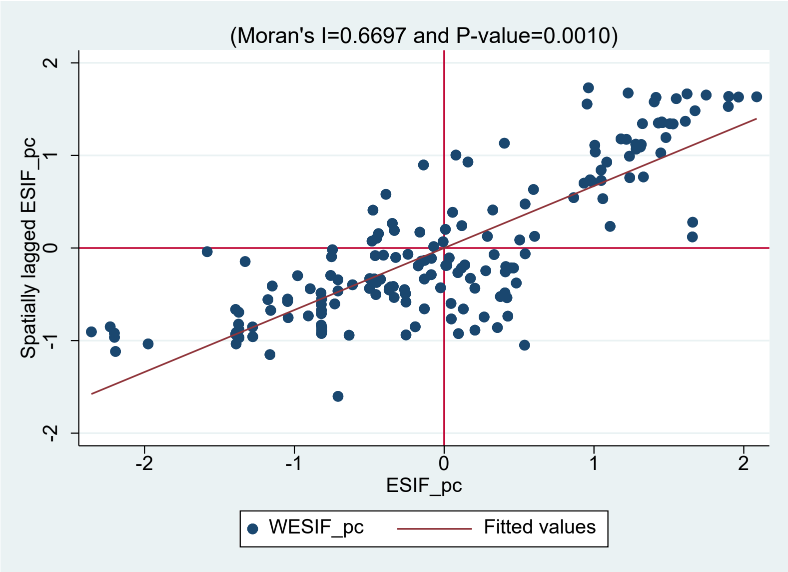


Figure A3
Moran´s I statistic test for the dependent variable

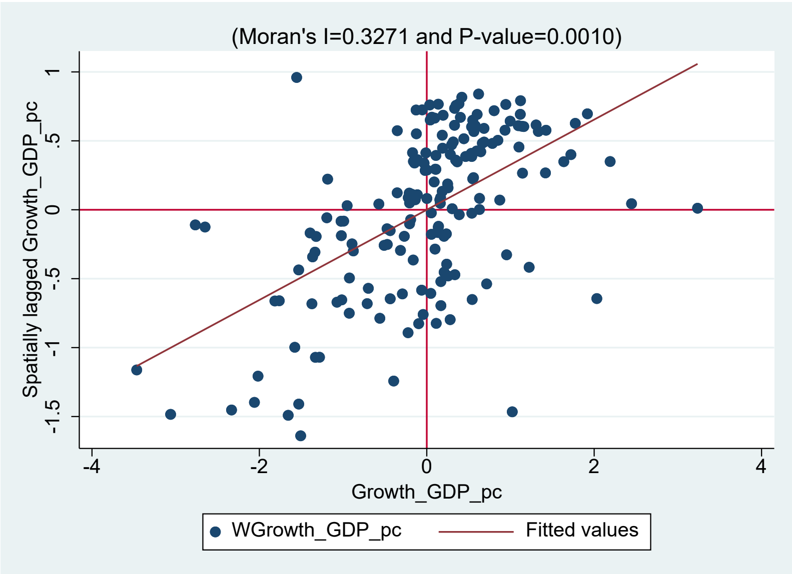
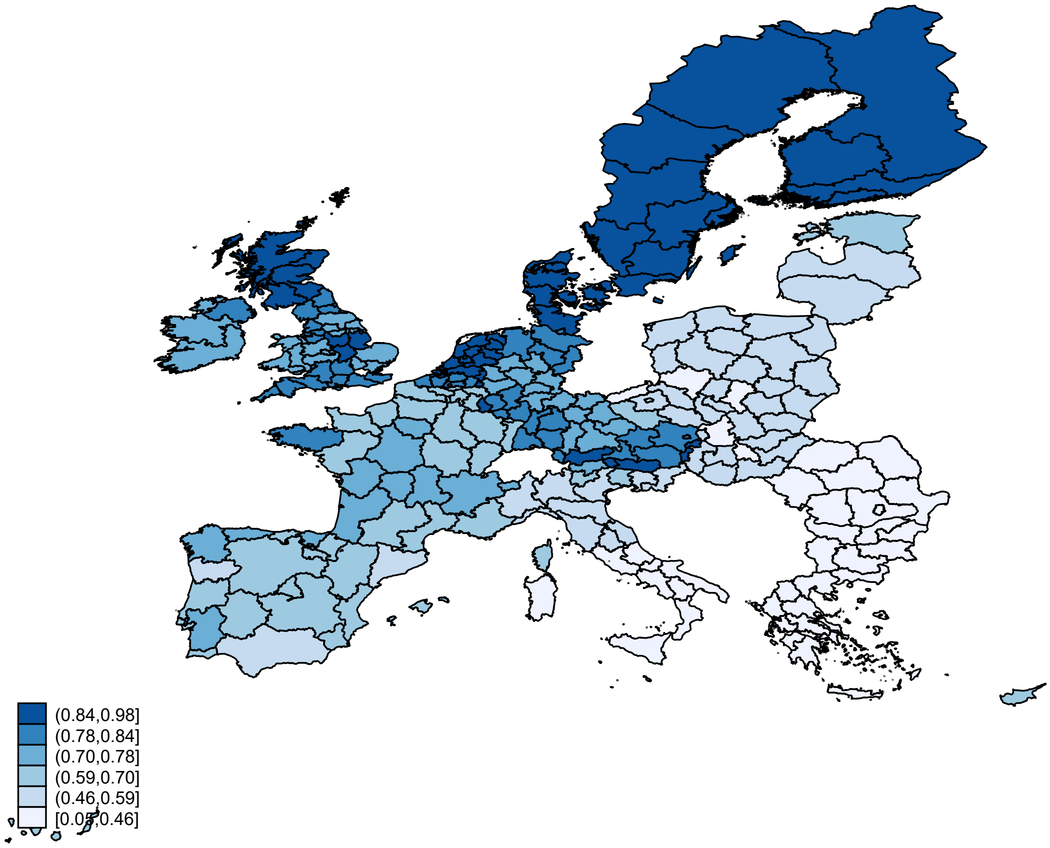


Figure A4
Geographic distribution of Quality of Government: 1996-2013



EconPol Europe

EconPol Europe - The European Network for Economic and Fiscal Policy Research is a unique collaboration of policy-oriented university and non-university research institutes that will contribute their scientific expertise to the discussion of the future design of the European Union. In spring 2017, the network was founded by the ifo Institute together with eight other renowned European research institutes as a new voice for research in Europe. A further five associate partners were added to the network in January 2019.

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1) sustainable growth and 'best practice',

2) reform of EU policies and the EU budget,

3) capital markets and the regulation of the financial sector and

4) governance and macroeconomic policy in the European Monetary Union.

Its task is also to transfer its research results to the relevant target groups in government, business and research as well as to the general public.