The Annals of Regional Science (2026) 75:1
https://doi.org/10.1007/s00168-025-01424-z

ORIGINAL PAPER

EU funds and TFP growth: how the impact changed over time and space

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Received: 4 April 2025 / Accepted: 30 September 2025

Abstract

The European Union's (EU) Cohesion Policy aims to reduce regional disparities through the European Structural and Investment Funds (ESIFs). While previous research has documented the positive effects of ESIFs on GDP growth, the role of regional capital accumulation in the growth process remains underexplored. To address this gap, the present study investigates the impact of ESIFs on regional performance by focusing on total factor productivity (TFP) growth as the outcome variable. TFP is computed by accounting for the highly heterogeneous patterns of capital accumulation across 262 NUTS2 regions over the period 2000–2019. Using annualised regional expenditure data, we assess the influence of fund allocation independently of EU programming periods. Our empirical strategy accounts for temporal heterogeneity by distinguishing three distinct phases: pre-crisis (2000–2008), crisis (2008–2014) and recovery (2014–2019). It also considers spatial heterogeneity by classifying regions according to their level of economic development. Furthermore, we disentangle the effects of the main funds—namely, the European Regional Development Fund (ERDF), the European Social Fund (ESF), the Cohesion Fund (CF), and the European Agricultural Fund for Rural Development (EAFRD). The results indicate that ERDF is positively associated with regional TFP, particularly during the 2014–2019 period, contributing to the reduction of productivity gaps between Eastern and more advanced regions. EAFRD enhances agricultural TFP growth, although primarily in regions that already exhibit high productivity levels. The remaining funds do not show statistically significant effects. These findings underline the importance of accounting for investment heterogeneity when evaluating the effectiveness of ESIFs and contribute to the broader policy debate on regional development strategies within the EU.

JEL Classification O47 · R11 · R58

The Authors are grateful to participants in the RSA 2023, AISRe 2023 and SIE 2023 conferences for their valuable comments and suggestions.

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Published online: 12 November 2025

1 Introduction

The European Union's (EU) Cohesion Policy has long been a fundamental pillar in addressing regional disparities and fostering economic convergence among member states. Aimed at mitigating structural imbalances, particularly in regions classified as "less developed", this policy channels financial support through the European Structural and Investment Funds (ESIFs). Reflecting the EU's strong commitment to this objective, approximately 500 billion euros were allocated to ESIFs between 2009 and 2018. Among these funds, the European Regional Development Fund (ERDF) is the main structural programme in terms of allocated financial resources (34.3% of all ESIFs in 2018). The European Social Fund (ESF) is dedicated to improving employability, fostering social inclusion, and supporting human capital investments. The European Agricultural Fund for Rural Development (EAFRD) promotes rural development and sustainable agriculture, while the Cohesion Fund (CF) seeks to reduce economic and social disparities in less-developed regions by financing investments in environmental and transport infrastructure. In 2014, the scope of ESIFs was further expanded with the introduction of the European Maritime and Fisheries Fund (EMFF), the Fund for European Aid to the Most Deprived (FEAD), and the Youth Employment Initiative (YEI), which support maritime and fisheries sustainability, combat material deprivation, and address youth unemployment in the most affected regions, respectively.

Over the past two decades, numerous studies have examined the impact of EU funds on regional economic performance (see, among many others, Becker et al. 2010; Rodríguez-Pose and Garcilazo 2015; Dall'Erba and Fang 2017; Gagliardi and Percoco 2017). While most of these studies indicate a positive effect of structural funds on regional GDP growth, their findings highlight significant variation depending on contextual factors and time periods.

Crucially, many of these contributions (a notable exception is Fiaschi et al. 2018) overlook the broader interplay of regional capital accumulation, due to both private investments—whose role is dominant in more advanced regions—and public expenditures from national or local governments. This is important because ESIF accounted for only 1.1% of Europe's total gross fixed capital formation during 2016–2018. Moreover, their share in total regional investments varies considerably across EU regions: in the Açores, ESIFs represent 26% of total investments, whereas in Île-de-France, they account for only 0.05%. This highlights the need to consider all sources of investment when assessing the impact of ESIFs.

This paper contributes to the current debate on the effectiveness of ESIF in driving regional performance by addressing these gaps in four key ways. First, we focus on total factor productivity (TFP) growth, rather than GDP per capita growth, as the primary outcome variable. This allows us to assess the impact of ESIFs while accounting for other important sources of investment that contribute to capital stock formation. Furthermore, TFP growth directly captures improvements in production efficiency, which EU funds aim to enhance through infrastructure, human capital, and technology investments. Such investments are expected to boost resource

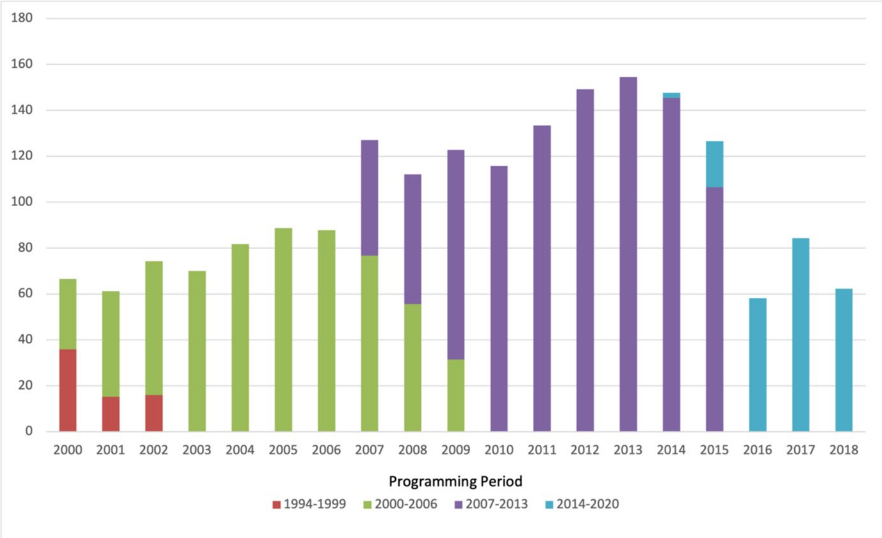

Fig. 1 ESIF expenditure per programming period, 2000–2018 (euro per capita, constant prices 2015)

allocation, improve business conditions, and support regional diversification into higher-value-added sectors.

Second, in our analysis, covering the period 2000–2019 and based on a sample of 262 NUTS2 European regions, we use annualised regional expenditure data from the European Commission's DG Regional and Urban Policy (EC 2017). This dataset allows us to assess the association of fund flows with TFP growth independently of programming periods. This represents a relevant advantage, as it enables the evaluation of impacts based on the resources actually accrued by the regions in a given year. As illustrated in Fig. 1, expenditures from different programming periods often overlap within the same year, given the possibility for the regions to spend the resources after the nominal ending of the programming period.[1] The continuity of funding across programming periods ensures that EU financial support is maintained without interruption. Therefore, accounting for the annual timeline of actual expenditure, regardless of the official programming period, permits a more accurate evaluation of the funds' effects.

Third, we address both temporal and spatial heterogeneity. It is important to highlight that the period under analysis encompasses major macroeconomic disruptions, most notably the 2008 global financial crisis and the subsequent European sovereign debt crisis, both of which had profound and asymmetric effects across EU regions. The use of expenditure data allows us to move beyond the conventional programming period framework and instead adopt a macroeconomic perspective that adequately accounts for the evolving economic landscape shaped by the two crises and their implications for the effectiveness of ESIFs. Thus, to address

[1] The n + 3 rules indicate the possibility to spend the funds three years after they have been committed. This implies that the programmes are actually implemented over a period of ten years rather than seven.

Table 1 Regions classification and total factor productivity in EU macro-areas

	More advanced regions	EU15 less-developed regions	EU13 less-developed regions	European Union
Number of regions				
2000–2008	164	44	38	246
2008–2014	183	26	53	262
2014–2019	196	16	50	262
Index TFP level, *EU* = 100				
2000	116	87	47	100
2008	117	83	51	100
2014	114	78	51	100
2019	112	82	55	100
TFP annual average growth rate, %				
2000–2008	0.88	0.43	2.81	1.09
2008–2014	0.08	− 0.65	0.43	0.08
2014–2019	0.56	1.02	2.02	0.86

EU15: Austria, Belgium, Denmark, Germany, Greece, Finland, France, Luxemburg, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, UK

EU13: Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia

Less-developed regions: regions whose per capita GDP is lower than 75% of the EU average in each programming period

For 2000–2008 and 2008–2019 we, respectively, employ 2000–2006 and 2007–2013 regions' classification

Bulgaria, Romania and Croatia are not considered in the first period

this issue, we consider three distinct phases: 2000–2008 (pre-crisis), 2008–2014 (financial crisis), and 2014–2019 (recovery phase).[2] In addition to temporal heterogeneity, we also examine territorial heterogeneity by classifying regions into three main subgroups: (i) more advanced regions,[3] (ii) less-developed regions within the countries that joined the EU until 1995 (EU15), and (iii) less-developed regions in countries that joined the EU after 2004 (EU13).[4] This approach accounts for both the varying stages of development and the economic and social disparities among European macro-areas.

Finally, we investigate the differentiated impact of the four main funds—ERDF, ESF, CF and EAFRD—which together accounted for 97% of total ESIFs in

[2] The definition and identification of these sub-periods are inherently subjective and should be interpreted with caution. Indeed, not all European countries experienced the crisis and the subsequent recovery along the same timeline. We will return to this issue in more detail in Sect. 5.3.

[3] More advanced regions include both "transition" and "more developed regions" (i.e. all regions with a per capita level of GDP above 75% of the EU average).

[4] Less-developed regions are those with a per capita GDP below 75% of the European average. The complete list of EU15 and EU13 countries is reported in Table 1.

2014–19. Particular attention is given to the sector-specific effects of EAFRD on agricultural productivity.

Our empirical strategy consists of two stages. First, we estimate a production function model with the traditional inputs—labour and capital—to compute regional TFP levels for 2000–2019. In the second stage, we assess the effects of EU funds on the TFP growth while controlling for key regional characteristics, including human capital, technological capital, institutional quality and population density.

Given the broad geographical coverage and extended time span of our dataset, we adopt a growth regression framework that, while not suited for causal identification through methods such as difference-in-differences (DiD) or regression discontinuity design (RDD), allows for a comprehensive analysis of the role played by ESIFs on regional TFP growth across the EU. To address potential endogeneity concerns, we complement this approach with an instrumental variables (IV) strategy and a carefully structured temporal specification of the models.

Our results indicate that the effectiveness of EU funding varies significantly across funds, regions, and time periods. We find that ERDF has a positive effect on regional TFP, particularly in the recovery phase 2014–2019, contributing to a narrowing of productivity gaps between eastern, less-developed regions and more advanced ones. When we focus on the impact of EAFRD on regional agricultural TFP growth, an interesting result emerges: the enhancing growth effect is found for regions with pre-existing high levels of agricultural productivity. As for the other funds, no positive association with regional TFP growth is detected.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the computation of regional TFP. Section 4 presents the ESIF distribution across EU regions and the regional contextual variables. Section 5 presents the main results of our growth models along with robustness checks based on IV estimation. Sections 6 and 7 provide two extensions, focusing, respectively, on the territorial heterogeneity of the ERDF and the impact of the EAFRD on agricultural productivity. The final section summarises the findings and discusses their policy implications.

2 Literature background

The European Union has progressively increased its budget allocation to regional Cohesion Policy, capturing the attention of scholars and public opinion. Despite the extensive academic debate, the economic literature has not yet reached a consensus on the economic impact of ESIFs.

Early contributions employed growth regressions using GDP as the dependent variable and revealed heterogeneous results that varied by period and regional subset (Fagerberg and Verspagen 1996; Cappelen et al. 2003). Dall'Erba and Fang's (2017) meta-analysis further identified factors contributing to this heterogeneity, including variations in research design, data characteristics, and the choice of regressors. Many studies relying on these models (e.g. Rodríguez-Pose and Garcilazo 2015; Pellegrini et al. 2013; Di Caro and Fratesi 2022) often fail to account for other sources of regional investment, leading to potentially underspecified models.

Notable exceptions include Fiaschi et al. (2018), who incorporated the regional average annual investment rate in their specification, and Albanese et al. (2021), who investigated ESIFs' impact on the TFP of southern Italian local labour markets. Furthermore, the prevalent use of aggregated ESIF measures in early studies has obscured potential differences in the impacts of individual funds.

More recent studies have adopted quasi-experimental approaches, specifically the regression discontinuity design (RDD), to achieve proper causal identification. These contributions have highlighted that regions classified as less developed—and therefore receiving more substantial financial support—tend to experience positive growth effects (e.g. Pellegrini et al. 2013; Becker et al. 2010; Gagliardi and Percoco 2017). However, despite methodological advances, these studies continue to focus almost exclusively on GDP-based outcomes, overlooking alternative dimensions of regional performance such as productivity. Moreover, they do not account for policy characteristics, such as heterogeneous funds' aims, temporal and, in most cases, also spatial distribution.

Both strands of literature have uncovered valuable insights, particularly on the role of regional contextual factors in influencing the effectiveness of ESIFs. Recent contributions show that their impact often depends on other regional factors, such as human capital, the quality of local institutions (Di Caro and Fratesi 2022; Incaltarau et al. 2020; Becker et al. 2013) and territorial capital (Bachtrögler et al. 2020). Moreover, ESIFs tend to produce stronger effects in industry and agriculture than in services (Coppola et al. 2023), suggesting the pivotal role of the sectoral composition of regional economies in mediating policy outcomes (Percoco 2017).

As a result, ESIF impacts remain highly heterogeneous across space. While the policy has proven effective in mature economies like Germany and the UK (Crescenzi and Giua 2020), evidence for weaker effects in Southern Italy is reported by Albanese et al. (2021) and Ciani and de Blasio (2015). Gagliardi and Percoco (2017) find that support is particularly effective in rural areas near urban hubs. Complementary findings suggest that Cohesion Policy may have also amplified intra-regional inequalities, especially where large urban agglomerations disproportionately benefited, as shown in the Spanish (López-Villuendas and del Campo 2024) and Greek (Psycharis et al. 2024) contexts. Nevertheless, Capello et al. (2025) showed that, at a broader territorial scale, the Cohesion Policy has contributed to reducing interregional disparities across EU regions.

Some recent contributions have focused on specific ESIF funds or axes, considering their specific aims and thus investigating their impact within a more detailed framework. The analysis of Mussida et al. (2023) represents a notable example: the authors have evaluated the impact of funding allocated through the ERDF and ESF under the thematic policy objectives "sustainable and quality employment" and "social inclusion" on material deprivation in the Spanish regions. Their approach, which accounted for individual and regional characteristics, revealed that interventions aimed at social inclusion effectively mitigate the risk of individual material deprivation. Insolda et al. (2025) investigated the role of EAFRD in the Italian context, focusing on the agricultural sector, finding a positive impact on the sectoral output and private investment but a negative impact on sectoral employment.

In this contribution, by using ESIFs expenditure data, we address the spatial and temporal heterogeneous impact of ESIF, trying to fill some of the identified gaps by considering a very comprehensive set of EU regions rather than focusing on specific countries. The concurrent role of other regional sources of capital accumulation is accounted for by employing TFP as the outcome variable. Moreover, we investigate the role of each fund on TFP growth, and we offer a more in-depth analysis of the impact of ERDF and EAFRD funds.

3 The computation of regional TFP

As highlighted in Sect. 2, most previous contributions on the impact of EU funds have overlooked other sources of investment, both private and public, that played an important role in shaping regional development. Although sizeable in absolute terms, ESIFs constitute a small part of total investments (nearly 1% in 2018) at the regional level. Thus, it is essential to account for the other relevant channels of capital accumulation when analysing ESIFs' effect on regional economic performance. An effective way of doing so is to assess the impact of EU funds on regional TFP rather than on GDP or labour productivity, as in most previous studies. As is well known, the computation of TFP is derived from estimating a production function, which accounts for the accumulation of total investment flows. Therefore, this approach allows for a more accurate assessment of the impact of ESIFs on regional performance.

Following Marrocu et al. (2022), we compute regional TFP levels using a quasi-growth accounting approach for the 262 NUTS2 EU regions (2010 version) included in our sample over the period 2000–2019.[5] We first estimate labour and capital elasticities from a Cobb–Douglas production function model rather than imposing them. Next, we compute the regional TFP levels by applying the quasi-growth accounting method using the estimated factors' elasticities, assumed invariant over the period under study.[6]

Figure 2.a shows the regional TFP levels in the initial year 2000 (index, EU = 100), while the regional TFP average annual growth rates for the 2000–2019 period are depicted in Fig. 2.b. The maps show very different productivity patterns among the EU macro-areas. Regions of Central-northern countries show high initial TFP levels and exhibit stable, albeit modest, TFP growth rates. In contrast, despite their lower initial productivity, regions of new accession countries display high and sustained growth rates. Notably, by 2019, more developed capital regions achieved TFP levels approaching the EU average, like Mazowieckie–Warsaw in Poland (index of 99), Prague in Czechia (91), and Cyprus (87). In contrast, while Southern regions

[5] We include the UK since it was part of the EU during the period under study. Malta is excluded given the lack of data for value added. The extra European territories of France, Portugal and Spain are also excluded.

[6] The estimation procedure of the Cobb–Douglas production function is presented in the Appendix, along with the computation of the capital stock series calculation. See Table 8 for the definition of variables and data sources.

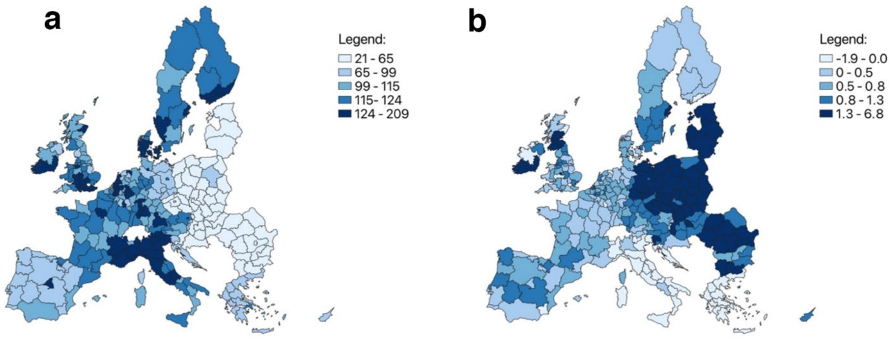

Fig. 2 **a** TFP level, 2000 (Index EU = 100). **b** TFP annual average growth rate, 2000–2019 (%)

initially exhibited TFP levels close to the EU average, with some highly productive areas such as Lombardy and Madrid, regions in Italy and Greece have experienced negative TFP growth over the period.

Under the Cohesion Policy framework, financial resources are mainly allocated to less-developed regions, defined as regions with a per capita GDP below 75% of the European average. The classification is revised for each EU programming period, reflecting changes in regional economic conditions to ensure that support is appropriately targeted. (Figure 5 in the Appendix shows less-developed regions for each programming period.)

Therefore, given the observed spatial pattern in Figs. 2a, b, we classify regions into three subgroups: (i) more advanced regions, (ii) less-developed regions in the EU15 and (iii) less-developed regions in the EU13. Additionally, we consider three distinct sub-periods to account for the economic impacts of the 2008 and 2011 financial shocks: the pre-crisis period (2000–2008), the crisis period (2008–2014) and the recovery phase (2014–2019).

The regions' classification and the TFP dynamics are presented in Table 1. Almost all regions within the EU13 new accession countries are included as less-developed areas: indeed, only the capital city regions Prague, Cyprus, and Bratislava were classified as more advanced during the programming period 2000–2007. At the same time, the number of less-developed regions in the EU15 central-northern regions has significantly decreased, falling from 13 in the first period to just two regions in the UK in the last one. The years 2008–2014 stand out for the lowest annual average growth rates across all subgroups, reflecting the severe impact of the financial crisis. TFP severely declined in EU15 less-developed regions. Conversely, EU13 less-developed regions show a positive, albeit moderate, annual average TFP growth rate, whereas more advanced regions display an almost stationary productivity dynamic.

The contrasting trajectories shown in Table 1 emphasise the heterogeneity of regional development across the EU and the sharp temporal heterogeneity. They reveal a pattern of productivity convergence in less-developed Eastern regions towards more advanced ones, contrasted with the stagnation of EU15 less-developed regions. These spatial and temporal heterogeneous economic dynamics across the

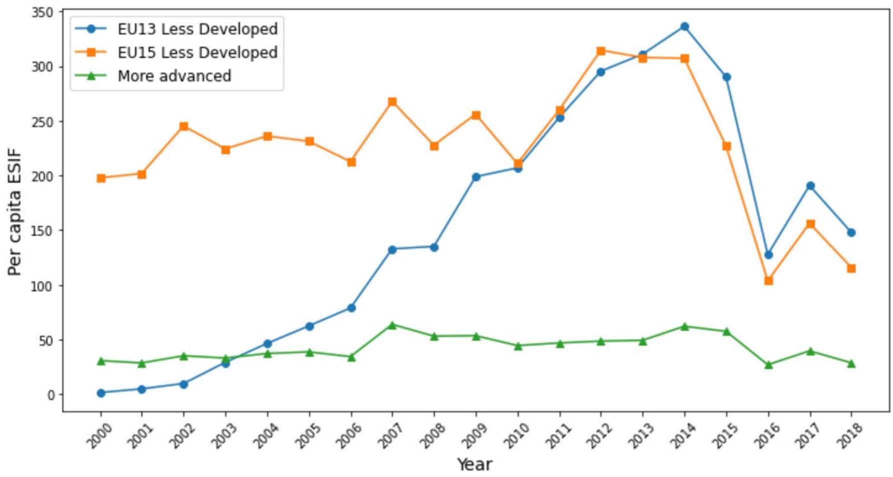

Fig. 3 ESIF expenditure per group of regions (euro per capita, constant prices 2015)

EU regions will be carefully addressed in our econometric analysis since we expect that the impact of ESIF on regional economic performance varies according to the development stage of the receiving regions and the period under consideration.

4 Data

4.1 European structural and investment funds

ESIFs are key EU regional policy instruments that promote economic, social and territorial cohesion. Although they are supposed to have a supply effect on GDP in the medium-long run term, they can also significantly influence TFP by addressing investment in crucial economic areas such as physical and digital infrastructure, human capital, new technologies adoption and collaborative networks, as well as providing support to streamline regulatory processes, reduce bureaucratic red tape and improve the ease of doing business. This way, ESIFs could lead to a more efficient allocation of resources and favour diversification into higher-value-added sectors, moving regions away from low-productivity industries.

Our analysis employs a novel dataset on ESIFs compiled by the Directorate-General for Regional and Urban Policy of the European Commission (EC 2017). This provides annualised regional-level expenditure data for the period 1986–2018 based on actual EC payments, representing a methodological advancement over previous studies that relied on commitment data. The distinction is critical, as commitments often diverge significantly from disbursed funds, as noted by Fratesi (2016). Importantly, the dataset exclusively captures EU payments, omitting national and regional co-financing. Furthermore, it enables the examination of annual expenditures independently of their original programming period—a key consideration given the frequent temporal overlap of expenditures across different funding cycles, as illustrated in Fig. 1 and discussed above.

Figure 3 displays the evolution of per capita ESIF expenditures across three macro-areas between 2000 and 2018. Expenditures in more advanced regions remained relatively stable throughout the period, whereas less-developed EU13 regions experienced a pronounced increase: from an average of just 1.3 euros per capita in 2000 to substantially higher levels by 2014 (336 euros). Around 2010, this spending converged with that observed in the less-developed areas of the EU15, mirroring the EU Cohesion Policy objective of channelling resources towards economically weaker regions. However, expenditures in these regions declined significantly after 2014, possibly because of delays in the payments related to the 2014–20 programming period.

Figure 4 shows the distribution of per capita ESIF across European regions in 2018. As expected, less-developed regions received an average of 139 euros per capita, far exceeding the 28 euros per capita allocated to more advanced areas. Funding was heavily concentrated in eastern Europe—Estonia reported the highest per capita amount (285 euros)—as well as in parts of southern Europe, particularly Portugal and Greece.

As we noted in the Introduction, ESIF comprise seven distinct instruments, of which four—ERDF, ESF, EAFRD and CF—account for approximately 97% of total allocations (see Table 2). The remaining three funds—the EMFF, FEAD and

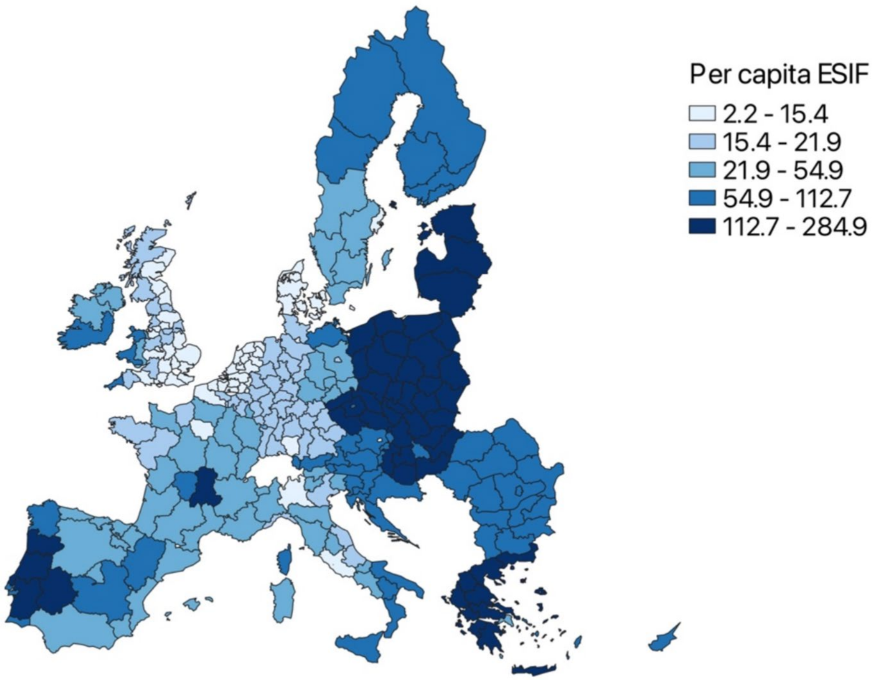

Fig. 4 ESIF expenditure across regions, 2018 (Euro per capita, constant prices 2015)

Table 2 EU funds (average % shares on total)

Fund		2000–2007	2008–2013	2014–2018
ERDF	European Regional Development Fund	53.7	43.2	38.1
ESF	European Social Fund	24.8	19.0	16.0
CF	Cohesion Fund	11.4	15.1	17.2
EAFRD	European Agricultural Fund for Rural Development	10.0	22.7	25.7
YEI	Youth Employment Initiative			1.9
FEAD	Fund for European Aid to the Most Deprived			0.6
EMFF	European Maritime and Fisheries Fund			0.5
	Total	100	100	100

YEI—were introduced only in the 2014–2020 programming period and represent a relatively small share of total funding. Consequently, our econometric analysis focuses exclusively on the four main funds. For simplicity, however, we continue to refer to their aggregate as ESIF. The eligibility criteria for these funds differ, leading to differences in financial allocation across macro-areas. Notably, the CF is allocated exclusively to Member States with a per capita Gross National Income below 90% of the EU-27 average. Therefore, for EU13 countries, the CF represents a significant proportion of total ESIF resources, accounting for 31% in 2018.

4.2 Regional contextual factors

As discussed in Sect. 2, several studies on ESIFs' economic impact have highlighted the pivotal role of some regional contextual factors. Intangible assets have been shown to influence regional economic performance and productivity growth (see, among others, Dettori et al. 2012; Peiró-Palomino 2016; Gumbau-Albert and Maudos 2022). In line with these findings, our analysis includes a set of such contextual variables, namely: regional endowment of human and technological capital, quality of institutions and population density. Detailed definitions and sources of these variables are reported in Table 8.

Human capital is measured as the percentage of people aged 25–64 with a tertiary education level (ISCED 5-6), reflecting the workforce's overall level of advanced skills. A well-educated labour force encourages the localisation of highly innovative firms, thereby exerting a significant influence on aggregate TFP. Its positive impact on regional and national economic performance has been discussed by a large body of literature (among others: Benhabib and Spiegel 1994; Murphy et al. 1991; Moretti 2004; Faggian et al. 2017).

Technological capital is included in terms of per capita R&D expenditure. This measure covers a broader range of innovative activities than patent-based measures, including those that do not lead to codified knowledge. Technological capital supports both product and process innovation (García-Pozo et al. 2021) and generates externalities that improve firm-level productivity, ultimately reinforcing regional economic performance (see Audretsch and Feldman 2004 for a comprehensive review).

The quality of the institutions at the regional level is mainly based on the European Government Quality Index developed by the University of Gothenburg (Charron et al. 2019), which covers corruption, impartiality and public service quality. This index has been available since 2013; thus, we extend the series backwards using the Worldwide Government Index of the World Bank Institute following the methodology of Charron et al. (2014). A high-quality government promotes the efficient allocation of public resources and the delivery of effective public services, thereby fostering local economic development (Rodriguez-Pose and Ganau 2022; Aresu et al. 2023).

Finally, population density allows us to control for possible agglomeration externalities, which may favour specialisations in specific sectors (Marrocu et al. 2013).

Table 3 presents the descriptive statistics for our contextual variables in 2000 and 2018, disaggregated by the three territorial groups. Generally, more advanced regions display higher values across all contextual factors. In terms of intangible assets, the gap between less-developed and more advanced EU15 regions has widened over time, whereas EU13 less-developed regions have shown a reduction in the gap for both human and technological capital.

5 Econometric modelling and results

5.1 Econometric modelling

As discussed in the previous sections, the aim of our analysis is to assess the role of ESIFs on regional TFP growth, which already accounts for other sources of regional capital accumulation, while controlling for a comprehensive set of regional contextual factors. Our analysis refers to the years 2000–2019, which are also divided into three sub-periods 2000–2008, 2008–2014, 2014–2019.

The analysis is conducted employing a regression growth model which, although not directly addressing causal identification, allows for examining key policy features, such as ESIFs' diverse objectives and their spatial and temporal heterogeneity.

For the whole period, we estimate the following panel specification:

Table 3 Regional contextual factors for macro-areas (index, EU = 100)

	More advanced regions		EU15 less-developed regions		EU13 less-developed regions	
	2000	2018	2000	2018	2000	2018
Human capital	113	108	90	67	69	79
Technological capital	149	126	36	31	13	16
Quality of institutions	109	108	95	79	82	77
Population density	115	111	80	106	88	69

See Table 1 for territorial classification

$$\Delta \mathrm{TFP}_{i,t-\tau} = \beta_0 + \beta_1 \mathrm{ESIFs}_{i\tau} + \sum_{j=2}^{5} \beta_j \mathrm{controls}_{ji\tau} + \beta_6 \mathrm{LD\_EU15}_{i\tau} + \beta_7 \mathrm{LD\_EU13}_{i\tau} + \beta_8 \mathrm{TFP}_{i\tau} + \delta_t + \upsilon_{i,t-\tau} \tag{1}$$

where the dependent variable ($\Delta TFP_{i,t-\tau}$) is the regional annual TFP average growth rate for 262 territorial units over three sub-periods, with $t = 2008, 2014, 2019$, and $\tau = 2000, 2008, 2014$, respectively. The windows considered are expected to smooth out potential short-term business cycle variations. Our variable of interest, ESIFs, is incorporated into the analysis on a log-transformed per capita basis, both in aggregate form and disaggregated into the four main funds—ERDF, EAFRD, ESF and CF—reflecting the expectation of differentiated effects on TFP growth. More specifically, we expect a positive effect, especially for the first two funds, as they are more directly meant to sustain productive activities, whereas the latter two might be more effective in enhancing broader social and environmental initiatives. As highlighted before, for each fund, we consider the total allocations, irrespective of the programming period, acknowledging that expenditure often overlaps across programming cycles, as previously discussed.

Contextual factors are included as control variables; they are log-transformed and entered at their initial-period values (τ), which is expected to mitigate possible reverse causality concerns. To distinguish between the three different territorial groups described in Sect. 3, we include the dummy variables *LD_EU15* and *LD_EU13*. Finally, the initial productivity level ($TFP_{i\tau}$) controls the regional convergence process, and it is expected to negatively affect its following growth rate.

As anticipated above, our analysis does not directly address causal identification. Estimating "true" causal effects of policy interventions on regional TFP growth in Europe is particularly challenging, given the inherent limitations of commonly used identification strategies. In this context, difference-in-differences (DiD) and regression discontinuity design (RDD) approaches are difficult to implement convincingly, as the necessary assumptions—such as parallel trends or sharp assignment rules—are rarely satisfied at the regional level.

Moreover, we think that endogeneity issues due to reverse causality are more likely to arise when modelling the level rather than the growth rate of TFP. It is worth highlighting that when modelling growth rates, region-specific unobserved heterogeneity is effectively removed because TFP growth rates are computed as differences of TFP log-levels. Notwithstanding these considerations, we aim to provide estimates which are as informative as possible on the driving role of ESIF in enhancing productivity growth. For this reason, ESIFs, as well as all control variables, enter the model with their initial-period values (at time τ). These lags—of at least five years—are expected to be sufficiently long to break any correlation with the error term, thereby addressing potential endogeneity concerns. Despite these precautions, a more in-depth analysis of endogeneity is provided in Sect. 5.4, where we assess the robustness of our main findings.

Table 4 EU funds and TFP growth. Dependent variable: TFP annual average growth rate

	Panel models		Cross-section models		
	(1)	(2)	(3)	(4)	(5)
	2000–2019	2000–2019	2000–2008	2008–2014	2014–2019
Total ESIF	0.0007				
ERDF	(0.0006)	0.0014***	0.0010*	0.0015*	0.0024**
		(0.0006)	(0.0005)	(0.0009)	(0.0011)
ESF		− 0.0006	− 0.0009	− 0.0024	− 0.0034*
		(0.0009)	(0.0008)	(0.0015)	(0.0019)
CF		− 0.0008**	− 0.0016***	− 0.0016**	0.0018*
		(0.0004)	(0.0004)	(0.0007)	(0.0010)
EAFRD		0.0000	− 0.0010	0.0001	0.0009
		(0.0007)	(0.0008)	(0.0012)	(0.0015)
Human Capital	0.0069***	0.0074***	0.0074***	0.0088***	0.0017
	(0.0013)	(0.0014)	(0.0016)	(0.0023)	(0.0030)
Technological Capital	0.0022***	0.0021***	0.0026***	0.0004	0.0010
	(0.0006)	(0.0006)	(0.0008)	(0.0012)	(0.0011)
Quality of Institutions	0.0069*	0.0064*	0.0098***	0.0194***	− 0.0088
	(0.0039)	(0.0040)	(0.0039)	(0.0064)	(0.0072)
Population density	0.0020***	0.0020***	0.0012**	0.0018**	0.0021**
	(0.0004)	(0.0005)	(0.0006)	(0.0009)	(0.0009)
EU15 less-developed	− 0.0022	− 0.0024	0.0013	− 0.0021	− 0.0003
	(0.0019)	(0.0020)	(0.0018)	(0.0034)	(0.0031)
EU13 less-developed	0.0061**	0.0072***		0.0085**	0.0043
	(0.0026)	(0.0028)		(0.0038)	(0.0046)
Initial TFP level	− 0.0164***	− 0.0175***	− 0.0244***	− 0.0132***	-0.0040

Table 4 continued

	Panel models		Cross-section models		
	(1)	(2)	(3)	(4)	(5)
	2000–2019	2000–2019	2000–2008	2008–2014	2014–2019
	(0.0030)	(0.0031)	(0.0040)	(0.0051)	(0.0067)
Adjusted R^2	0.2742	0.2799	0.5473	0.2104	0.2924
Observations	729	729	205	262	262

All right-hand side variables are per capita, log-transformed and refer to the initial year of the period considered

EU13 regions are not included in the first sub-period 2000–2008

Time dummies included in panel models

Robust standard error, in parentheses

Significance levels: ***(1%), **(5%), *(10%)

5.2 Panel results

The results for the panel estimation over the period 2000–2019 are reported in the first two columns of Table 4. In column (1), ESIFs are considered as an aggregate single fund, and they exhibit a positive but non-significant coefficient. Meanwhile, the contextual variables—human capital, technological capital, institutional quality and population density—all show significant coefficients with the expected signs, indicating their effectiveness in capturing other determinants of TFP growth, possibly correlated with ESIFs. The initial TFP level presents a negative and significant coefficient, signalling a convergence process whereby less productive regions tend to grow faster. After controlling for regional contextual factors, the positive and significant coefficient for the EU13 less-developed regions, coupled with the non-significant coefficient for the EU15 less-developed regions, is also evidence of the closing gap between the former group of regions and the more advanced ones.[7]

When we distinguish the four main ESIFs (column 2), a different and more engaging picture emerges: the ERDF fund has a positive coefficient, whereas the CF has a negative one; the EAFRD and the ESF do not seem to affect total TFP growth.

For robustness, we have also estimated models in which our measure of technological capital, R&D, was replaced by the stock of patent applications presented at the European Patent Office (Eurostat 2011; Maraut et al. 2008; OECD 2009) and quality of institutions by an index of social capital. The main results for the variables of interest remained unchanged. We have also included a measure for production specialisation on knowledge-intensive services, but it did not exhibit a significant coefficient.[8]

The estimated ERDF coefficient implies a non-negligible effect on the level of TFP in the long run: a 10% increase in ERDF investments entails an increase in total productivity of around 0.8%. This result indicates that the ERDF is effective at promoting regional productivity growth, most likely through its focus on infrastructure development, support for small and medium-sized enterprises (SMEs), and investment in innovation and technology, which directly impact the productivity and competitiveness of regions.[9]

The not statistically significant coefficients for EAFRD and ESF seem to indicate, in line with evidence provided by Coppola et al. (2024) for the Italian context, that they do not have an enhancing effect on overall TFP growth. It is important

[7] When a single dummy variable for less-developed regions is included instead of separate dummies for EU15 and EU13 less-developed regions, its coefficient is not statistically significant. This result highlights the importance of distinguishing between the two areas to capture heterogeneity in TFP growth dynamics.

[8] All results of the robustness exercises are available from the authors upon request.

[9] It is worth remarking that we have also performed Granger-causality tests on ERDF, which is the most relevant fund within ESIFs. For all the specifications considered in this section (both panel and sub-periods), we regressed the current level of ERDF on past TFP growth rates. In all cases, the regressors' coefficients turned out to be not significant (all results are available from the authors upon request). Although these tests are not meant to rule out reverse causality in strict sense, the not significant results indicate that past TFP growth rates do not exhibit any predictive power on the current amount of ERDF. Such evidence further mitigates endogeneity concerns.

to note that these funds pursue distinct policy objectives—such as social inclusion in the case of ESF and enhancing competitiveness in the agricultural sector for the EAFRD—which may not primarily focus on boosting aggregate production efficiency. Moreover, during the period under examination, two severe financial crises disrupted local economies worldwide. In response, ESF and CF allocations were largely directed towards supporting employment and reinforcing resilience, particularly in lagging behind regions. This might have had adverse effects on efficiency.

5.3 Temporal heterogeneity

As previously outlined, there are relevant temporal changes that affect our analysis. Eastern countries joined the EU in 2004, receiving substantial financing only afterwards. Additionally, the subprime global crisis in 2008 and later the sovereign debt crisis had a significant economic impact across Europe. Hence, we identify three sub-periods: the pre-crisis years (2000–2008),[10] the global financial crisis followed by the sovereign debt crisis (2009–2013), and the recovery phase (2014–2019). This breakdown allows us to better evaluate the potential temporal differences in the ESIFs' economic impact.

Columns (3)–(5) of Table 4 display the empirical results disaggregated by sub-period and fund. A key finding is that the ERDF coefficient is positive and significant across all three sub-periods, with its effect strengthening over time and reaching its highest level during the recovery phase. Specifically, a 10% increase in per capita ERDF during this phase corresponds to a substantial 6% rise in TFP, highlighting the importance of these policy-driven interventions.

This outcome may be attributed to the 2014–2020 Cohesion Policy reforms (EU 2013), which emphasised support for innovation, the digital and green transitions and SMEs, notably through initiatives like the Smart Specialisation Strategy (Foray, 2009; Marrocu et al. 2023). The reformed policy also introduced a stronger results-oriented approach, simplified regulatory procedures and conditionalities for funding. These elements appear to have played a key role in revitalising EU economies (EC 2024; Serafini et al. 2025; Santos et al. 2023).

Regarding the other funds, the CF exhibits negative and significant coefficients in the first two sub-periods, turning positive during the recovery phase. The unexpected negative effect in the initial period may stem from the fact that only Greece, Spain, Portugal and Ireland were eligible for CF support at the time. Furthermore, as the fund is primarily aimed at supporting environmental objectives and infrastructure development, its impact on productivity may manifest over a longer time horizon than that considered in our analysis. This result contrasts with the positive and statistically significant effect estimated for the 2014–2019 period, when the sample includes both EU15 and EU13 regions—the latter having become major recipients of CF support only after 2007. To explore potential territorial heterogeneity in the fund's impact, we augment the model for this later period by

[10] In the 2000–2008 period, the EU13 regions are not included since they did not receive relevant EU funds.

introducing an interaction term between CF and a dummy variable identifying the three EU15 beneficiary countries Greece, Spain and Portugal (see column 1 of Table 10 in the Appendix).[11] The CF coefficient remains positive and significant, suggesting a favourable effect on TFP growth in EU13 regions benefiting from the fund. By contrast, the negative and significant interaction term points to a weaker impact in the three EU15 countries. This pattern is consistent with Di Comite et al. (2018), who show that Cohesion Policy investments in transport infrastructure have been particularly effective in stimulating growth in Eastern regions by enhancing accessibility. Conversely, in countries like Spain, a portion of the EU-funded infrastructure was perceived as redundant or misaligned with regional needs, raising concerns about inefficiency and limited territorial effectiveness (Medeiros 2017).

By contrast, the coefficients associated with the other funds remain statistically insignificant in the sub-period analysis, consistent with the results obtained from the full panel specification. A noteworthy exception emerges for the European Social Fund (ESF) during the 2014–2019 period, where its coefficient is negative and statistically significant. This finding is somewhat unexpected and warrants further consideration. It is important to note that the primary policy objective of the ESF—emphasised in the 2014–2020 Cohesion Policy reform—is to foster social inclusion across the EU. Specifically, the ESF supports interventions aimed at improving access to employment, enhancing labour mobility, supporting marginalised communities, investing in education and training, and strengthening institutional capacity. These goals are primarily oriented towards improving social cohesion and human capital outcomes, such as reducing disparities and increasing employability (Fusaro and Scandurra 2023), rather than directly stimulating growth in TFP.

Regarding the agricultural fund, although the EAFRD coefficient is not statistically significant, it shifts from negative in the first period to positive thereafter, suggesting a possible change in its influence. Given the specificities of the agriculture sector, the role of EAFRD will be examined in Sect. 7 with respect to its own sectoral TFP.

As noted in the Introduction, defining the years 2008–2014 as a unified "crisis period" may be open to debate, given the heterogeneous timing of the financial crisis and subsequent recovery across European countries. Between 2010 and 2013, after the global financial crisis, some countries in the EU (Greece, Ireland, Portugal, Spain, Italy) were affected (to varying degrees and at different times) by a second shock: the sovereign debt crisis. In contrast, other member states (like France, Belgium, and the Netherlands) experienced only a moderate slowdown, while the Eastern European countries exhibited persistent growth. To account for these divergent patterns, we re-estimate the model for the sub-period 2008–2014, introducing a dummy variable for the five countries most affected by the sovereign debt crisis (column 2 in Table 10). The dummy coefficient turns out to be statistically insignificant. However, the estimates for our main variables of interest remain robust, including the positive and significant effect of ERDF. The only notable change is that the

[11] It is worth noting that Ireland did not receive CF resources during the 2014–2020 programming period, as its Gross National Income (GNI) per capita exceeded 90% of the EU average.

negative coefficient associated with ESF becomes statistically significant, confirming its specific goals highlighted before. As a further robustness check, we re-estimate the model excluding the year 2014 and thus considering the period 2008–2013. Main results are virtually unchanged (column 3 in Table 10).

The sub-periods analysis also allows us to observe how the convergence process varied over time: the estimated coefficient for the initial TFP level reveals that convergence was faster during the first period, while it slowed down during the second and stagnated during the recovery phase. Interestingly, the estimated coefficients for regional contextual factors are not statistically significant during the recovery phase (2014–19) when regional productivity growth appears to have been primarily driven by the funds' financial support.[12]

5.4 Robustness checks based on IV approach

Before discussing the extensions of our analysis, in this section we present an in-depth investigation of our main specifications with respect to endogeneity concerns.

As argued in Sect. 5.1, estimating causal effects of policy interventions on regional growth is very difficult, not only due to the limitations of applying the DiD or RDD approaches across all 262 EU NUTS2 regions, but also because the instrumental variable (IV) estimation method faces substantial obstacles. Finding credible and valid sources of exogenous variations, i.e. the variables which affect the outcome only through the treatment, is exceptionally difficult. Caselli et al. (1996) and Temple (1999) emphasised the scarcity of suitable instruments, as most candidate variables are at risk of being endogenous in growth model settings. A possible exception is the morphological structure of a country's geography. In practice, the use of weak or invalid instruments may introduce more bias and inconsistency than standard least-squares estimation, ultimately leading to unreliable inference. Therefore, while acknowledging that the issue of potential endogeneity may also affect our analysis, we adopt a cautious empirical strategy aimed at mitigating bias without resorting to instruments of questionable validity.

Following Caselli et al. (1996) and Dall'Erba and Le Gallo (2008), we adopt a geography-based instrumental variable, which is the inverse distance (in km) between Brussels and each region included in our sample. This instrument is considered relevant because ESIFs are distributed spatially according to a centre-periphery pattern. Since our analysis considers four distinct EU funds, we require at least three additional instrumental variables to estimate the models presented in Table 4. Following Dall'Erba and Le Gallo (2008) and Kennedy (2008), we use the rank order of the lagged values of each fund as a potential instrument. These instruments satisfy the relevance condition, as they are, by construction, correlated with the explanatory variables. Given the lag structure, they are also supposed to be uncorrelated with the current error term. As our analysis employs five instrumental variables, we test for their joint exogeneity by carrying out the test for overidentifying restrictions.

[12] When we extended the analysis to the period 2019–22, a period strongly affected by the Covid-19 pandemic, the results indicated no significant effects for all the funds considered. This might be due to the pervasive effects of the pandemic disruptions and to the fact that most of the ESIF funds were redirected to provide income and health-system support.

Table 5 EU funds and TFP growth—IV estimates. Dependent variable: TFP annual average growth rate

	Panel models			Cross section models		
	(1)	(2)	(3)	(4)	(5)	(6)
Time structure	3 sub-periods	6 sub-periods	6 sub-periods	2000–2008	2008–2014	2014–2019
ERDF	0.0014***	0.0018***	0.0012**	0.0009*	0.0022**	0.0019*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0010)
ESF	– 0.0004	– 0.0019**	– 0.0012	– 0.0004	– 0.0031**	– 0.0024
	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0018)
CF	– 0.0009**	– 0.0012***	– 0.0007	– 0.0016***	– 0.0017**	0.0018*
	(0.0004)	(0.0004)	(0.0013)	(0.0004)	(0.0007)	(0.0010)
EAFRD	0.0001	– 0.0005	– 0.0007	– 0.0007	– 0.0009	0.0011
	(0.0008)	(0.0007)	(0.0006)	(0.0009)	(0.0012)	(0.0015)
Controls	yes	yes	yes			
Time dummies	yes	yes	yes	–	–	–
Country dummies	no	no	yes	–	–	–
First-stage F tests						
ERDF	2296.99	2441.58	2159.86	1154.75	1292.89	998.46
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ESF	588.31	1522.66	1833.19	177.55	455.38	459.71
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CF	955.48	1246.04	358.74	572.95	2096.67	455.73
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EAFRD	397.01	423.39	433.71	69.12	126.74	1052.58
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hansen J test	1.010	0.829	2.433	2.267	0.097	0.438
	(0.3148)	(0.3625)	(0.1188)	(0.1321)	(0.7559)	(0.5083)
Adjusted R^2	0.2795	0.3252	0.3616	0.5457	0.2060	0.2900
Observations	729	1401	1401	205	262	262

Instrumental variables: inverse distance from Bruxelles, rank order for each lagged EU Fund

Controls: Human and technological capital, quality of institutions, population density, initial TFP level, EU15/EU13 less-developed dummies

Panel models. Column (1): 2000–08, 2008–14, 2014–19. Columns (2) and (3): 2000–03, 2003–06, 2006–09, 2009–12, 2012–15, 2015–19

All right-hand side variables are per capita, log-transformed and refer to the initial year of the period considered

EU13 regions are excluded in column (1) and (4) for 2000–2008, and in columns (2) and (3) for the first three sub-periods

Robust standard error, in parentheses

Significance levels: ***(1%), **(5%), *(10%)

The main results of the IV analysis are reported in Table 5. Column (1) presents the IV estimates corresponding to model (2) in Table 4. Overall, the new estimates confirm previous findings, highlighting the effectiveness of ERDF in enhancing TFP growth. Previous results on the other funds, as well as on the control variables, are also corroborated.[13] It is worth noting that the results of the first-stage F tests show that the set of instruments is relevant, while the Hansen J test indicates that the joint null hypothesis on the instruments' exogeneity cannot be rejected.

To assess the robustness of our main results with respect to the panel time structure, column (2) of Table 5 reports estimates from a six-period panel specification. In this case, the dependent variable is computed over shorter sub-periods of 3 years each, except for the final sub-period which covers four years.[14] All right-hand side variables are measured at the initial year of each sub-sample, and the set of instruments is recomputed to account for the new lag structure. The new results provide further support for the effectiveness of ERDF, which now exhibits a slightly larger coefficient. The main difference compared to the previous specification concerns the ESF, which becomes statistically significant at the 5% level. First-stage F tests and the Hansen J test confirm the adequacy of the instruments used in model (2).

In column (3), we conduct an additional robustness test to assess whether the results are influenced by potential remaining unobservable heterogeneity. To this end, we augment model (2) by including a wide set of country dummies.[15] Even with a now highly saturated model, the ERDF coefficient remains statistically significant, although its magnitude decreases to 0.0012—implying a long-term effect of 0.046% for a 10% increase in the fund amount. None of the other funds display statistically significant coefficients. The results of the first-stage F tests and the Hansen J test are similar to those previously discussed.

Finally, in the last three columns of Table 5, we test the robustness of our main results across the sub-periods proposed in the previous section to analyse the intertemporal heterogeneity. Using the same kind of instruments as above, IV estimates continue to support our main findings. More specifically, ERDF shows a positive and significant coefficient in all sub-periods. Notably, in the last sub-period, both ERDF and CF attain statistical significance at the 10% level, marking an improvement relative to the corresponding results in Table 4.

Overall, the IV approach, combined with a richer temporal structure in the panel models, confirms that our main results are robust with respect to serious endogeneity concerns and offer valuable evidence on the role of ESIF funds in promoting TFP growth across the EU regions. A proper causal analysis, based on DiD or RDD approaches, is left to future research, where the focus will shift to narrower subsets of regions observed at a finer spatial scale.

[13] Note that results are very similar also in the case in which we consider only the set of instruments based on the ranks of the explanatory variables.

[14] We have not considered shorter sub-periods to avoid undue effects from business cycle dynamics.

[15] Dummies are included for all the countries (19) with at least three NUTS2 regions. Results are very similar in the case the entire set of country dummies is included in the model.

Table 6 ERDF and TFP growth in regional subsets and sub-periods. Dependent variable: TFP annual average growth rate

	(1) 2000–2008	(2) 2008–2014	(3) 2014–2019
ERDF	0.0011**	0.0010	0.0018*
	(0.0005)	(0.0008)	(0.0009)
ERDF * EU15 less-developed	0.0003	− 0.0003	− 0.0002
	(0.0003)	(0.0007)	(0.0006)
ERDF * EU13 less-developed		0.0023***	0.0016*
		(0.0008)	(0.0009)
Other Funds	− 0.0013***	− 0.0015***	0.0002
	(0.0003)	(0.0006)	(0.0009)
Controls	yes	yes	yes
Adjusted R^2	0.5488	0.2238	0.2644
Observations	205	262	262
Linear combinations			
EU15 less-developed	0.0014***	0.0007	0.0015
	(0.0005)	(0.0009)	(0.0014)
EU13 less-developed		0.0033***	0.0034**
		(0.0012)	(0.0014)

All right-hand side variables are per capita, log-transformed and refer to the initial year of the period

Controls: Human and technological capital, quality of institutions, population density, initial TFP level

EU13 regions are not included in the first sub-period 2000–2008

Robust standard error, in parentheses

Significance levels: ***(1%), **(5%), *(10%)

6 ERDF and territorial heterogeneity

In Sects. 3 and 4.1, we documented notable differences in productivity trends and fund allocation among EU regions, suggesting that ESIF impacts may vary spatially. Moreover, Table 1 illustrates that less-developed regions exhibit distinct economic dynamics depending on their territorial position, while divergent regional objectives may also lead to varying outcomes. Di Comite et al. (2018) emphasised that ESIFs have significantly contributed to the development of new transport infrastructure in emerging EU regions. This strategic choice has strengthened economic relationships between peripheral eastern territories and central European manufacturing hubs, thereby reshaping the EU economic framework. Therefore, in this section, we examine in detail the funds effects considering the territorial heterogeneity of the European regions.

Given that the ERDF is the more sizeable fund and the only one showing a consistently positive impact on regional TFP growth over the three periods, our spatial heterogeneity analysis focuses on this fund. We investigate differential effects by introducing in Table 6 interaction terms between ERDF and spatial dummies for

EU13 less-developed and EU15 less-developed regions, while aggregating the other three funds in the "Other funds" variable.

Table 6 reveals pronounced spatial and temporal heterogeneity. In the first period, the ERDF had a positive and statistically significant effect across all regions considered,[16] with no significant differences detected for EU15 less-developed regions. Between 2008 and 2014, an interesting result emerges: while the ERDF coefficient is not significant for either advanced regions or EU15 less-developed ones, a positive and significant differential effect (0.0023) is detected for less-developed regions in EU13 which obtain an overall effect of 0.033. These findings suggest that, during the financial crisis, the benefits of ERDF support accrued primarily to the less-developed regions of the EU13. This pattern may reflect a deliberate strategic reorientation of ESIF priorities aimed at mitigating the crisis's adverse effects on the most vulnerable territories. The experience of subsequent shocks—such as the COVID-19 pandemic and the energy and inflation crises triggered by the Russia–Ukraine war—further underlines the critical importance of appropriately reallocating EU funds effectively to enhance regional resilience and cohesion in times of systemic stress.

During the recovery phase, the ERDF continued to yield significant positive effects, with an estimated coefficient of 0.0018 for advanced regions. While no significant differences are found for less-developed territories in the EU15, those in the EU13 continue to exhibit stronger performance. With a differential impact of 0.0016, their overall effect reaches 0.0034. This more pronounced impact suggests that the fund has contributed to narrowing the productivity gap between advanced and EU13 less-developed regions.

Overall, since their accession, EU13 less-developed regions have benefited substantially from ERDF allocations, while advanced regions have experienced consistent productivity gains, except during the crisis period. In contrast, EU15 less-developed regions benefited only in the initial sub-period; after the financial crisis, they underperformed, as indicated by non-significant ERDF coefficients. This underperformance, concentrated in territories located in Portugal, Spain, Southern Italy and Greece, may be attributed to structural challenges, including limited human capital, low institutional quality (Aresu et al. 2023; Incaltarau et al. 2020), and a shift in EU priorities that increasingly favoured the economic integration of newer eastern member states over less-developed areas within the EU15.

Our results not only complement prior research highlighting the positive effects of Cohesion Policy for less-developed regions (Becker et al. 2010; Pellegrini et al. 2013), but also reinforce the empirical evidence on the spatial heterogeneity of these effects across the EU. By examining a comprehensive set of regions, our findings corroborate and extend the heterogeneity patterns documented by Di Caro and Fratesi (2022) and Crescenzi and Giua (2020), who focused on a more limited subset of EU territories.

[16] It is important to note that the EU13 new accession countries are excluded from the first period, as they did not receive significant cohesion funding from the European Union during that time.

7 EAFRD and agricultural productivity

The analysis of ESIF has revealed a positive and significant, albeit highly heterogeneous, impact of ERDF on regional TFP growth. In contrast, other funds have not shown a positive effect on regional productivity growth. These findings highlight the need for more targeted analyses of funds that pursue specific objectives, which should be evaluated using alternative frameworks and outcome variables.

This section focuses on EAFRD and investigates its impact on regional agricultural productivity growth. As shown in Table 2, financial allocations to this fund have steadily increased, reinforcing the importance of conducting a more focused assessment of its economic impact.

EAFRD replaced the Guidance Section of the former European Agricultural Guidance and Guarantee Fund (EAGGF), the so-called second pillar of the Common Agricultural Policy (CAP), in 2007 under EC(2005a). According to EC(2005b), the EAFRD finances initiatives aimed at improving "the competitiveness of agriculture and forestry; the environment and the countryside; and the quality of life and management of economic activity in rural areas". More details on the characteristics of the fund can be found in Soldi (2016).

In this context, we assess EAFRD impact following the same methodological framework employed in Sect. 5. Using sectoral data on value-added, employment and gross fixed capital formation, we first compute the agricultural regional TFP annual average growth rates as in Sect. 3, including country dummies instead of regional fixed effects. The estimated elasticity is around 0.54 for both the capital stock and the labour input.

The descriptive statistics for agricultural TFP (Table 9) reveal a more complex and varied temporal and spatial pattern compared to overall TFP. A preliminary analysis based on the previously used regional categorisation proved inadequate to capture this complexity. Therefore, we address territorial heterogeneity by accounting for initial conditions, as the initial level of agricultural regional productivity may play a pivotal role in determining the effectiveness of the fund.

Considering the high temporal heterogeneity identified in the previous analysis, we report the impact of EAFRD separately for each sub-period. The main results are presented in Table 7. In this analysis, we not only control for human capital and the quality of institutions, as in the previous sections, but also incorporate sector-specific control variables. Specifically, we include the regional number of patent applications in the agricultural field submitted to the European Patent Office (EPO) as a proxy for sectoral technological capital and the revealed comparative advantage (RCA) index in the agricultural sector, based on sectoral employment. A strong concentration of employment in agriculture may signal a reliance on traditional production structures, potentially limiting the scope for productivity-enhancing shifts towards higher-value-added activities. Overall, the coefficients of contextual variables exhibited the expected sign, except for the quality of institutions, for which we obtained a negative coefficient despite being significant only in the last sub-period.

Table 7 EAFRD and agricultural TFP growth. Dependent variable: agricultural TFP annual average growth rate

	(1) 2000–2008	(2) 2008–2014	(3) 2014–2019	(4) 2000–2008	(5) 2008–2014	(6) 2014–2019
EAFRD	0.0064***	0.0033	0.0038	0.0045*	0.0049	0.0027
	(0.0022)	(0.0035)	(0.0049)	(0.0027)	(0.0033)	(0.0051)
EAFRD * TFP lowest quartile				0.0034	– 0.0087**	– 0.0029
				(0.0024)	(0.0036)	(0.0044)
EAFRD * TFP highest quartile				0.0023	0.0070*	0.0073*
				(0.0034)	(0.0038)	(0.0043)
Agriculture technological capital	0.0318***	– 0.0123	0.0222	0.0319***	– 0.0079	0.0211
	(0.0103)	(0.0089)	(0.0142)	(0.0101)	(0.0091)	(0.0142)
RCA_{Ag}	– 0.0920***	– 0.0453**	0.0097	– 0.0945***	– 0.0401**	0.0039
	(0.0186)	(0.0200)	(0.0286)	(0.0195)	(0.0204)	(0.0274)
Human capital	0.0097	– 0.0010	0.0005	0.0093	– 0.0030	– 0.0021
	(0.0066)	(0.0080)	(0.0133)	(0.0067)	(0.0080)	(0.0137)
Quality of institutions	0.0003	0.0190	– 0.0711*	– 0.0020	0.0221	– 0.0694**
	(0.0192)	(0.0171)	(0.0366)	(0.0193)	(0.0191)	(0.0341)
Initial agriculture TFP level	– 0.0487***	– 0.0474***	– 0.0191*	– 0.0477***	– 0.0786***	– 0.0415*
	(0.0060)	(0.0127)	(0.0108)	(0.0094)	(0.0224)	(0.0237)
Adjusted R^2	0.410	0.189	0.087	0.408	0.233	0.092
Observations	205	262	262	205	262	262
Linear combinations						
TFP lowest quartile				0.0079***	– 0.0039	-0.0003
				(0.0031)	(0.0051)	(0.0066)
TFP highest quartile				0.0068**	0.0119***	0.0099*
				(0.0032)	(0.0042)	(0.0058)

All right-hand side variables are per capita, log-transformed and refer to initial year of the period considered

EU13 regions not included in the first sub-period

Robust standard error, in parentheses

Significance levels: ***(1%), **(5%), *(10%)

Our variable of interest, EAFRD, shows a positive coefficient in all sub-periods, although it is significant only in the pre-crisis one (0.006).[17] This temporal variation may be influenced not only by the financial crisis but also by the Fischler reform of 2003 EC (2003), which redirected a higher percentage of funds from the first

[17] When a panel model for the entire period is estimated, the coefficient is positive (0.003) but not statistically significant.

pillar of the CAP (direct farmer support) to the EAFRD, further targeting rural infrastructure and sectoral innovation technologies (Insolda et al. 2025).[18]

To deepen our understanding of the temporal heterogeneity of our findings, we refine the analysis by examining EAFRD impact across regions with different initial levels of agricultural productivity. Regions were categorised into three groups: lowest productivity (1st quartile group), highest productivity (4th quartile), and those with productivity levels within the interquartile range. Accordingly, we re-estimated the sub-period models by introducing interaction terms between EAFRD funding and indicators for the highest and lowest initial TFP quartiles.

Results are presented in columns (4)–(6) of Table 7. The estimates confirm a positive and significant effect of EAFRD (0.0045) during the pre-crisis period, with no significant differences across regions with varying levels of initial TFP. However, following the financial crisis and the Fischler reform, the estimated coefficients for regions within the interquartile range of initial productivity become non-significant in the last two sub-periods. Less productive regions even exhibit a negative and statistically significant differential effect during the crisis period, which becomes non-significant in the final period. In contrast, only the most productive regions (4th quartile) display a positive and significant differential effect of EAFRD, which tends to increase over time, even if the total effect amounts to 0.012 in the second sub-period and to 0.01 in the final one.

Overall, the results indicate that the EAFRD effectively stimulates productivity growth primarily in regions with already high levels of agricultural productivity, particularly after the financial crisis and the Fischler reform. In these regions, EAFRD funding may have complemented existing strengths, amplifying its impact on productivity. The Fischler reform, which aimed to enhance the competitiveness of the agricultural sector, may have further contributed to this dynamism by disproportionately benefiting regions that were already well-positioned for growth.

In contrast, EAFRD's impact on productivity growth in less productive regions is notably limited. While it does not exhibit a significant positive effect on sectoral TFP growth in these areas, it may still generate other benefits, such as supporting farm incomes. Many of the lowest TFP regions are concentrated in Eastern Europe, where, following EU accession, the productive systems underwent profound restructuring. This transformation involved a shift in specialisation from agriculture to low-tech manufacturing. Meanwhile, western regions redirected low-tech activities eastward and focused on high-tech, knowledge-intensive sectors, including precision farming, leveraging advancements in green technologies (Marrocu et al. 2013).

In EU13 less-developed regions, administrative absorptive capacity remains limited, and the paying agencies encounter difficulties in converting programme allocations into reimbursable expenditures (Raicov et al. 2021), particularly due to the prevalence of small, fragmented farm structures. Weak governance of the agricultural payment agencies can hinder the formation of local partnerships and complicate ex-ante evaluations, thereby increasing transaction costs for potential rural beneficiaries. In such contexts, reallocations of resources towards short-term crisis

[18] Financial flows under the first pillar of the CAP are not included in the analysis. To the authors' knowledge regional data covering all European countries is not publicly available, limiting the scope of this analysis.

responses risk displacing long-term productivity-enhancing investments, precisely the kind of structural support that low-performing rural areas require most.

The long-term orientation of EAFRD investments, designed to gradually enhance the competitiveness and sustainability of the agricultural sector, may require extended timeframes for their effects to fully materialise, particularly in the aftermath of economic crises and amid the ongoing reconfiguration of production structures. This transformation is increasingly influenced by global megatrends, including the restructuring of global value chains and the twin green and digital transitions. For less productive regions, these dynamics underline the critical need to reinforce technical assistance, strengthen administrative absorptive capacity and invest in the upskilling of farmers and rural SMEs. Such measures are essential to ensure that these territories can fully capitalise on the opportunities offered by EU funding instruments, especially in a period marked by intensified global uncertainty.

8 Conclusions and policy implications

This study investigates the relationship between ESIFs and regional TFP growth, offering a more rigorous and comprehensive analysis than previous research. Our contribution is fourfold. First, we adopt TFP growth—rather than the more commonly used GDP per capita growth—as the outcome variable. This choice enables us to capture the influence of both EU-funded and domestic investment on regional productivity, thereby providing a more accurate assessment of ESIFs' effectiveness. Second, we employ expenditure data instead of commitment data, allowing us to estimate the effects of financial resources that regions have actually absorbed and utilised, rather than those merely allocated on paper. Third, we explicitly account for the temporal and territorial heterogeneity of EU funding by disaggregating the analysis across fund types, time periods and regional classifications. Fourth, our empirical analysis spans the years 2000 to 2019 and encompasses a comprehensive sample of 262 NUTS2 regions, representing one of the most extensive and detailed assessments of ESIFs' impact to date. Finally, it is worth noting that our results have undergone a series of robustness checks. Although our growth regression approach, combined with the broad geographical coverage and long time span of the sample, did not allow for the application DiD or RDD methods to identify causal effects, we thoroughly addressed endogeneity concerns by employing an IV estimation strategy, along with a carefully specified temporal structure for the models.

Our results indicate that the effectiveness of ESIFs is highly context-dependent and exhibits substantial variation over time. Among the different funds, the ERDF stands out as the principal catalyst of regional productivity growth. Its impact is especially marked in the less-developed regions of the EU13 member states, particularly during the post-crisis recovery period. This enhanced effectiveness can be attributed to the reform of the Cohesion Policy, which placed greater emphasis on innovation, digital transformation and SME support. Nevertheless, persistent challenges remain. The redirection of resources during financial crises and the continued underperformance of less-developed regions within the EU15 underline the urgent need for more tailored, adaptive and resilient funding strategies in an era of mounting global pressures.

In response to the COVID-19 pandemic, ESIF resources were reallocated to strengthen healthcare systems and provide support to SMEs (EU 2020a). Further regulatory flexibility allowed for the reprogramming of funds across regional priorities (EU (2020b)). More recently, structural funds have also been deployed under the Repower EU initiative to address the energy crisis stemming from the Russia–Ukraine conflict. While such reallocations are often justified by urgent needs, they also carry the risk of diverting resources away from the ERDF's core objectives of promoting regional development and convergence. Looking ahead, it will be crucial to evaluate the post-COVID performance of EU funding—once longer time series become available—to determine whether the effectiveness of these instruments has been restored or further eroded in the aftermath of successive crises.

The specific evaluation of the EAFRD indicates that its ability to stimulate agricultural productivity depends on regions' initial productivity levels: we detect a positive effect in regions with high levels of agricultural productivity (mainly in the EU15 countries), while the influence is notably limited in less productive regions (mainly in the Eastern countries). This finding suggests that a one-size-fits-all approach is unlikely to meet the diverse needs of rural areas and highlights the importance of designing targeted interventions that account for regional structural differences.

Based on our results, we propose several policy recommendations. First, to sustain the ERDF's core objectives of fostering long-term regional convergence and economic growth, future programming periods should continue emphasising innovation and digitalisation while maintaining an appropriate balance with crisis-response initiatives. Second, addressing persistent disparities—particularly in underperforming regions—requires targeted capacity-building efforts, improvements in institutional quality and investments in human capital. Third, the heterogeneous impact of the EAFRD highlights the importance of designing policies that are tailored to the distinct structural features of regional agricultural sectors. More specifically, in the EU's least productive rural areas, a carefully calibrated policy mix is required, combining front-loaded technical assistance, extended implementation horizons and sustained investment in farmers' skills and local governance capacities.

Finally, future research should continue to distinguish between the distinct effects of each ESIF fund on regional economic performance. As demonstrated by our evaluation of the EAFRD, funds must be assessed considering their specific policy objectives, with carefully selected outcome variables that capture their targeted impacts. Moreover, as Capello and Cerisola (2024) emphasise, more granular territorial data, particularly at the NUTS3 level, are essential for assessing intra-regional disparities and understanding the distributional effects of EU funding. To facilitate this line of research, it is crucial that the EU Commission makes more disaggregated territorial data publicly available.

Appendix 1. Computation of Total Factor Productivity at the regional level

Following Marrocu et al. (2022), we compute regional TFP levels using a quasi-growth accounting approach. We first estimate labour and capital elasticities from a Cobb–Douglas (CD) production function, and then we compute the regional TFP levels for 2000–2019 by applying the growth accounting method using the estimated factor elasticities, assumed invariant over the considered period.

The CD is log-linearised as follows:

$$\ln\left(GVA_{it}\right) = \beta_K \ln\left(K_{it}\right) + \beta_L \ln\left(L_{it}\right) + \alpha_{\mathrm{i}} + \delta_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \qquad (2)$$

where $i = 1,\ldots N$ (262 regions); $t = 2000, \ldots, 2019$ (20 years); GVA is Gross Value Added, K is capital stock, and L are units of labour; α_{i} are regional fixed effects, δ_{t} are times dummies, and $\varepsilon_{\mathrm{it}}$ is the error term. The procedure to construct the capital stock is described in section A2.

To deal with the usual production function endogeneity problem, we apply the fixed-effects two-stage least-squares (2SLS) estimation method, employing the one-year lagged input factors as instrumental variables. Similar results are obtained using the two-year lagged factors as instruments. The estimated elasticities are 0.3 for the capital stock and 0.62 for the labour input.

Appendix 2. Capital stock computation

Since the lack of data on regional capital stock, the series has been built by employing data on national capital stock published by the IMF (sum of public, private and PPP capital stock) (2017). To fully exploit the IMF dataset, for the 11 Centre-North and four Southern countries, we use series for 1990–2020 by computing the initial value of capital stock in 1989 as the mean value of the national capital stock for 1988–1989. For the other 12 new accession countries, the series has been calculated for 2000–2020, computing the initial value in 1999, considering the annual mean value of national stock for 1996–1999.

The capital stock initial value at the regional level has been computed using the methodology proposed by Gleed and Rees (1979): the initial regional value is based on the regional share of investments (weight 0.75) and the regional share of labour units (weight 0.25) for 1988–1989 for the first group of countries and 1996–1999 for the other. Initial regional capital values have been measured in constant prices (2015) employing the AMECO deflator. The rest of the series have been calculated using the perpetual inventory methodology, which states that the value of the capital stock at time *t* is equal to the value at time *t-1*, augmented by investment measured at time *t* and diminished by depreciation (we assume a 10% depreciation rate). The series of the stock of capital is expressed in constant euros 2015 to avoid variations caused by inflation.

Appendix 3. Tables and Figures

See Tables 8, 9, 10 and Fig. 5

Table 8 Variables definitions and sources

Variable	Label	Description	Primary source
Value added	GVA	Gross VA, constant values at 2015 price	EUROSTAT
Labour units	L	Units	EUROSTAT
Gross fixed capital formation	GFCF	Constant values at 2015 price	EUROSTAT
Capital stock	K	Constant values at 2015 price	Own calculation
Total factor productivity	TFP	Estimated index	Own estimation
European Structural and Investment Funds	ESIF	Sum of all funds, per capita values (constant price 2015)	European Commission
European Regional Development Fund	ERDF	Per capita values (constant price 2015)	European Commission
European Social Fund	ESF	Per capita values (constant price 2015)	European Commission
European Agricultural Fund for Rural Development	EAFRD	Per capita values (constant price 2015)	European Commission
Cohesion Fund	CF	Per capita values (constant price 2015)	European Commission
Human capital	HK	% people 25–64 years with a tertiary education level (ISCED 5–6)	EUROSTAT
Technological capital	TK	R&D expenditure, per capita (constant price 2015)	EUROSTAT
Quality of institutions	QI	Quality of institutions composite index	Univ. Gothenburg, World Bank
Population density	PD	Resident population per square km	EUROSTAT
Patent applications	PAT	Stock of patent applications at European Patent Office per 100,000 inhabitants	Maraut et al. (2008); OECD (2009); Eurostat (2011)
Social capital	SK	% people who have worked in a volunteer organisation	Own elaboration on European Social Survey (ESS ERIC)
Production structure	RCA	Revealed comparative advantage, various sectors, based on employment data	EUROSTAT
Agriculture technological capital	ATK	Patent applications at European Patent Office per 100,000 inhabitants in group A01	OECD

Table 9 Agriculture total factor productivity in EU regions

	EU more advanced regions	EU15 less-developed regions	EU13 less-developed regions	European Union
Index TFP level, EU = 100				
2000	108	112	52	100
2008	111	97	64	100
2014	110	89	63	100
2019	108	93	69	100
TFP annual average growth rate, %				
2000–2008	1.19	− 0.63	4.55	1.38
2008–2014	0.35	1.18	− 0.07	0.35
2014–2019	− 1.44	0.62	0.67	− 0.91

Table 10 Robustness checks on sub-periods and funds. Dependent variable: TFP annual average growth rate

	Country differences for CF	Country differences during crisis	
	(1)	(2)	(3)
	2014–2019	2008–2014	2008–2013
ERDF	0.0020**	0.0016*	0.0016*
	(0.0010)	(0.0009)	(0.0010)
ESF	− 0.0030	− 0.0026*	− 0.0023
	(0.0019)	(0.0015)	(0.0016)
EAFRD	0.0009	0.0002	0.0001
	(0.0015)	(0.0012)	(0.0012)
CF	0.0037***	− 0.0020***	− 0.0018**
	(0.0014)	(0.0008)	(0.0008)
CF * D3	− 0.0032*		
	(0.0016)		
D5 countries		0.0029	
		(0.0027)	
Controls	yes	yes	yes
Adjusted R^2	0.3105	0.2104	0.1897
Observations	262	262	262

All right-hand side variables are per capita, log-transformed and refer to the initial year of the period considered

Robust standard error, in parentheses

Significance levels: ***(1%), **(5%), *(10%)

Controls included as in Table 4

D5: Dummy for the five countries (Greece, Ireland, Italy, Portugal, Spain) effected by the sovereign debt crisis

D3: Dummy for the three EU15 countries (Greece, Portugal, Spain) that received CF in 2014–2019

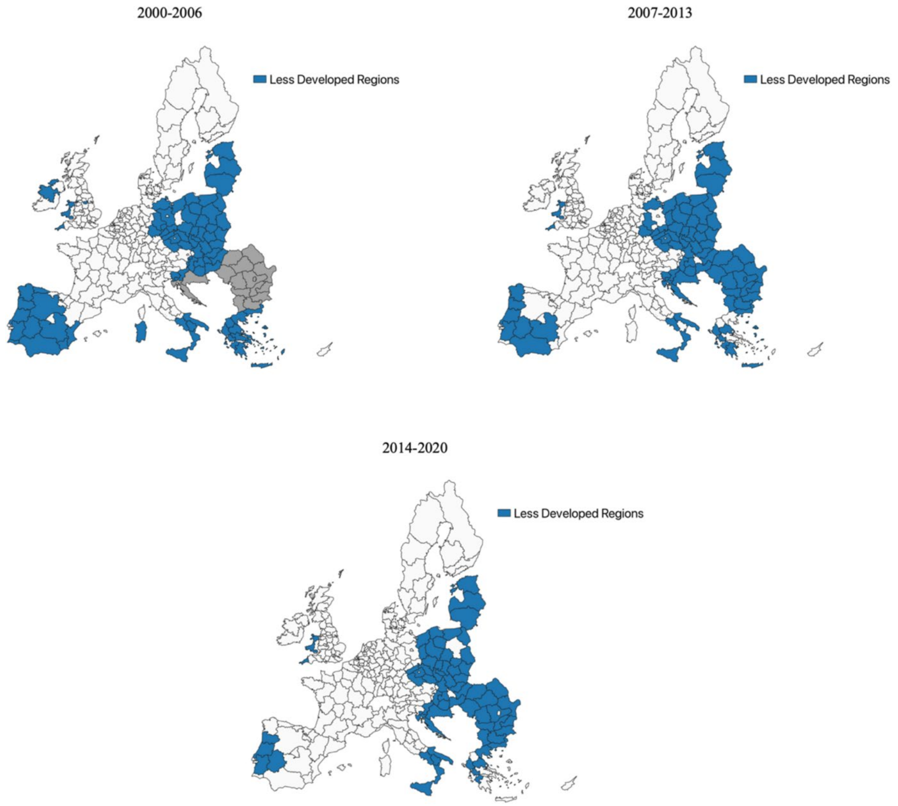

Fig. 5 Less-developed regions for programming periods (NUTS2 2010 version)

Author contribution All authors contributed equally to the conception, design, execution and writing of this work.

Funding Open access funding provided by Università degli Studi di Cagliari within the CRUI-CARE Agreement. Funding provided by EU Horizon Project ESSPIN "Economic Social and Spatial Inequalities in Europe in the Era of Global Mega-Trends" (project n. 101061104).

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

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