The economic impact of Structural and Cohesion Funds across sectors: immediate, medium to long term effects and spillovers

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Abstract

The EU Cohesion Policy has progressively diversified the financed sectors, with possible heterogeneous impacts on local growth. However, the literature is still largely oriented to the analysis of aggregate impacts. Our study offers a granular investigation of the sectoral impacts of Structural and Cohesion Funds on European NUTS 2 over the period 2007-2014. We find that expenditures in energy, R&D, and transportation sectors stimulate higher GDP per capita growth with persistent effects, coherently with reduction of production costs, higher accessibility and innovation in recipient regions. These effects are enhanced when expenditures are more diversified across sectors. Spatial panel models show that transport sector generates the highest spillovers, leveraging on agglomeration and proximity, while at geographical level we find substantial spillovers cross-cutting national boundaries. From a policy perspective, our analysis suggests how spatial and sectoral effects can contribute to the design of a more effective allocation of the EU budget.

Keywords: — Structural and Cohesion Funds, GDP per capita growth, spillovers, economic impact, NUTS 2

Acknowledgements

We thank the 19^{th} Annual European Economics and Finance Society Conference 2021, the organization committee and related participants for the useful suggestions and comments to improve the research. We are grateful to the Editor, Associate Editor and two anonymous referees for their comments and suggestions that significantly contribute to improve our work. The usual caveats apply.

1 Introduction

Structural and Cohesion Funds (SCFs) constitute a cornerstone of EU Regional Cohesion Policy aiming to reduce disparities and promote convergence. The interest on the impact of this program of financial support has progressively increased given the extension in the scope of SCFs and the growth of the total EU budget (Bachtler et al., 2018). Shifting from period 2000-2006 to 2007-2013, the amount of SCFs in fact rose more than 60% from 241 to 390 billion euros. In addition, the composition of these funds was renovated[1], with the European Agricultural Guidance and Guarantee Fund (EAGGF) replaced in 2006 by the European Agricultural Fund for Rural Development (EAFRD) and the European Agricultural Guarantee Fund (EAGF), enlarging the objectives of funding resources from the financial support of the agricultural sector to the stimulus of economic growth in rural lagging areas. Moreover, completely new initiatives emerged, such as the Youth Employment Initiative (YEI) launched in 2014 to support education, training, apprenticeships and job placements in areas where youth unemployment was higher than 25%, confirming a dynamic evolution of EU investment strategies.

Due to the wide variety of projects financed through SCFs, the EU Regional Cohesion Policy has been defined as a "do it all policy". Hence, policy makers are currently focused on the economic impact of investments across different sectors, since heterogeneous levels of local development may be achieved depending on the economic activity in which the EU transfers are allocated. Treating different government spending in alternative sectors as a homogeneous compound may induce mixed results, since different sectors might have a different role in stimulating economic growth (Blanchard and Perotti, 2002; Cortuk and Guler, 2015). Indeed, investments in certain sectors might have immediate positive effects, while other types of investments might generate a significant impact only in a long term perspective (Scandizzo et al., 2020). Moreover, the magnitude of economic multipliers might be different across sectors and dependent on the level of diversification and complementarity of expenditures (Aschauer, 1989; Auerbach and Gorodnichenko, 2012; Venables et al., 2021).

Understanding synergies of investment programmes targeting different sectors has always been a major challenge in the strategic management of SCFs. In a review of existing studies on the impact of SCFs, Pieńkowski and Berkowitz (2016) highlight that previous analyses neglected

[1] See: `https://cohesiondata.ec.europa.eu/Other/Historic-EU-payments-regionalised-and-modelled/tc55-7ysv`.

the growth effects of expenditures in different development axes, thus encouraging the use of data on EU transfers broken down by investment category to deal with this goal.

Against this background, we assess the economic impact of EU SCFs expenditures across different sectors in NUTS 2 regions.[2] The main contribution of this paper is twofold. First, we analyse the immediate short term effect generated by these funds through the application of a Generalized Propensity Score Matching (GPSM) framework with continuous treatment variables (Hirano and Imbens, 2004) to identify the causal impact of SCFs in specific sectors. We complement this finding by studying the impact of SCFs at different time lags analysing also medium-long term effects and providing evidence on the time span required by SCFs expenditures in different sectors to generate local development. In this way, we contribute to fill a relevant gap in the literature as, to the best of our knowledge, this is the first work that attempts to distinguish these effects with respect to the sectors financed by SCFs. The majority of previous studies has focused in fact on the impact of transfers in their aggregate amount without explicitly taking into consideration the targeted sectors (see, e.g., Puigcerver-Peñalver et al. 2007; Dall'Erba and Le Gallo 2008; Esposti and Bussoletti 2008; Mohl and Hagen 2010; Fiaschi et al. 2018). After more than 30 years from the launch of the European Regional Cohesion Policy in its current form, we thus perform an evaluation of the effectiveness of the EU budget spending to assess the economic results generated by transfers in different sectors. Given current contingencies, our purpose appears particularly relevant for policy makers, as the strategy adopted by the European Commission (EC) to tackle the current economic crisis generated by the COVID-19 pandemic is based on the Recovery Fund, the largest stimulus package ever provided by the EU budget to boost economic recovery. Our study supports the identification of the most promising sectors for an appropriate distribution of the EU budget (Botta et al., 2020; Arbolino and Di Caro, 2021).

Second, we investigate whether SCFs activate relevant spillovers, identifying NUTS 2 regions contributing more to the emergence of benefits that cross cut the boundaries of the country in which they are generated. This analysis can support a more effective allocation of SCFs through the identification of regions mainly contributing to a cross fertilisation of other member states

[2] Nomenclature of Territorial Units for Statistics (NUTS) is a standard geocode adopted by the EU to refer to subdivisions of countries for statistical purposes. A three-level hierarchy of NUTS is established for each EU country, with NUTS 1 representing the most aggregate level, NUTS 2 the intermediate level and NUTS 3 the highest level of geographical granularity. In the rest of the paper we use either the term NUTS 2 or NUTS 2 regions to identify these subdivisions of EU countries.

economies. We distinguish from previous works, which estimate externalities associated with aggregate SCFs (Dall'Erba and Le Gallo, 2008; Le Gallo et al., 2011; Fiaschi et al., 2018), since we disentangle the spillovers generated by SCFs expenditures in specific sectors, having the possibility to identify more precisely the mechanism through which these funds are beneficial not just for the administrative units receiving them, but also for similar regions in terms of geographical and technological proximity. With this regard, we further contribute to extant literature by considering both geographical distance and technological proximity, addressing some of the pitfalls of existing literature that adopts parameters of spatial dependence which are simplistic in comparison to the complex trade, capital and people flows actually taking place between regions (Pieńkowski and Berkowitz, 2016).

To achieve these purposes, we analyse the impact of EU SCFs on the economic growth of 258 NUTS 2 regions over the time frame 2007-2014, through the application of cross-section and spatial-panel models.

We find that *Energy*, *Human Resources*, *R&D* and *Transportation* constitute the most promising sectors where to allocate funds, as they have a significant and positive impact on economic growth. In addition, we show that SCFs are more effective in regions that receive more *diversified* transfers across sectors, providing evidence that complementary and coordinated investment strategies produce stronger increases in GDP per capita. On the other hand, *Environment* expenditures do not have a significant immediate effect on regional development but a positive impact at different time lags, suggesting that this type of expenditure requires time before to contribute to local development. A similar pattern is observed for SCFs in *IT infrastructures*, *Rural Development* and *Tourism* sectors, while for the *Social Infrastructures* sector we do not find any significant effect.

In terms of spatial spillovers, we find that the strongest indirect effect is generated by the Transportation sector. At geographical level we find substantial spillovers cross-cutting national boundaries, but with heterogeneous distribution among European countries. For instance, UK retains the largest portion of indirect effects within country, generating only 6.6% and 4.8% of spillovers toward France and Ireland, respectively. Spain absorbs almost 60% of indirect effects generated by Portugal, while Austria, Belgium, France, Germany and the Netherlands generate a large amount of spillovers cross cutting national boundaries, with only a percentage between 13% and 38% absorbed by NUTS 2 in the same country. Overall, regions producing the largest externalities are concentrated in Belgium, while regions inducing the lowest spillovers are located in Cyprus, Ireland, Italy, Malta, Spain, Sweden and UK.

The paper is structured as follows: Section 2 provides an overview of the β-convergence models adopted in this literature and discusses the relevance of investigating the impact of SCFs across different sectors. Sections 3 and 4 present the data and the methodology used for the empirical analysis, respectively. In Section 5 we estimate cross-section, panel and spatial models and we present the main results. Section 6 concludes discussing main contributions and limitations of this study.

2 The effects of EU funds on economic growth

Empirical works analysing the contribution of EU funds to regional economic growth are mainly based on the so-called β-convergence models, formally derived by Barro and Sala-i Martin (1992) from the neoclassical growth theory[3].

Despite the rich set of studies investigating the effects generated by EU transfers, empirical evidence provides mixed, if not contradictory, results. Puigcerver-Peñalver et al. (2007) showed a positive effect of SCFs on growth rates of Objective 1 regions in the period 1989-1993, but not in the years 1994-1999. Kyriacou and Roca-Sagalés (2012) highlighted the existence of a maximum desirable level of SCFs transfers (approximately 1.6% of national GDP) beyond which they may increase regional differences within countries.

Conversely, other authors identified no statistically significant impact of SCFs on convergence, highlighting how disparities persist in EU since EU transfers mainly induce industry relocation effects (Dall'Erba and Le Gallo, 2008). Finally, depending on the model specification, SCFs can provide a limited or even negative contribution to economic growth (Esposti and Bussoletti, 2008; Mohl and Hagen, 2010).

These empirical studies analyse the impact of aggregate SCFs without distinguishing the

[3] An alternative stream of literature exploited causal methods (i.e. Regression Discontinuity Design, Difference in Differences and Synthetic Control Method) to assess the economic impact of SCFs (Ferrara et al., 2017; Gagliardi and Percoco, 2017; Cerqua and Pellegrini, 2018). These approaches have been used to investigate the effect of EU transfers on Objective 1 regions, namely NUTS 2 with a GDP per capita below 75% of the EU average, with respect to not treated administrative units. The majority of these studies is coherent in providing evidence of a positive immediate impact of these funds on GDP per capita growth (Becker et al., 2010; Pellegrini et al., 2013), while the benefits tend to vanish as the treatment is stopped (Barone et al., 2016; Becker et al., 2018). Moreover, the effectiveness of SCFs is found to be related to the local economic structure, human capital endowment and quality of government institutions (Becker et al., 2013; Percoco, 2017).

main sectors in which financial transfers are allocated. The main exception is represented by RodrÍguez-Pose and Fratesi (2004) that over the time frame 1989-1999 investigate the impact of SCFs investments on different development axes in Objective 1 regions. They highlight that expenditures in infrastructure and business support do not generate significant economic growth, while agriculture transfers have a short term positive impact, and investments in the education sector are associated with long term benefits. However, their analysis relies on still highly aggregated data, considering that business support SCFs includes also expenditures in the tourism sector and that investments in the infrastructure development axis encompass expenditures on transportation and environment projects, hampering the possibility to disentangle the impact of EU transfers allocated to specific sectors.

In our work we provide a finer representation on the impact of SCFs expenditures across different sectors on a more recent programming period, contributing to the discussion on the immediate and medium-long term effects generated by different types of SCFs expenditures for which extant literature has not developed a solid consensus.

Furthermore, existing studies on SCFs are characterized by two additional potential pitfalls. First, they mainly focus on the immediate impact of SCFs, neglecting medium-long terms effects associated with these investments. Barone et al. (2016) and Becker et al. (2018) show that benefits produced by SCFs in less developed regions may vanish as the treatment is stopped. However, they consider aggregate SCFs, while long term positive tangible economic value might be associated to only some specific sectors. For instance, infrastructure projects may need the conclusion of the construction phase and the start of the operating period in order to boost local economy (Alotaibi et al., 2021). Social and environmental investments contributing to a more sustainable society may have a significant impact on regional development in a long term perspective, while R&D investments might require some years before developing applicable business solutions stimulating economic growth (Prettner and Werner, 2016).

Second, a wide portion of extant studies does not model spillovers that might be generated by SCFs investments in different sectors, activating mechanisms of economic growth not only in the recipient regions, but also in the neighbours NUTS 2. Theoretical reasons suggesting the necessity to consider spatial effects are related to economy integration, trade, capital mobility, labour migration, technology transfer and knowledge spillovers, which demonstrate that regions cannot be considered as isolated entities.

Although spatial econometric models show a strong potential for the study of the impact of SCFs on economic growth, and neglecting spatial dependence might provide unreliable estimates, there is a limited amount of empirical works that have exploited them (López-Bazo et al., 2004; Ramajo et al., 2008; Arbia et al., 2010). Fiaschi et al. (2018) identify relevant spillovers produced by SCFs during the time frame 1991-2008 in a sample of 12 EU countries, and Philippe and Simone (2021) confirm this finding for the next programming period, showing that by 2030, around 30% of the impact of Cohesion Policy will be accounted by spillovers. Conversely, Le Gallo et al. (2011) find absence of relevant externalities over the period 1989-1999 analysing 12 EU countries. These heterogeneous results might be partially explained not only by the different considered NUTS 2 regions or analysed time frames, but also by the investments sectors in which SCFs have been allocated, as they might have a different potential in generating spillovers. For instance, knowledge transfers and technology spillovers tend to activate higher innovation levels, raise productivity and stimulate firms growth (Bottazzi and Peri, 2003; Ramos et al., 2010; Autant-Bernard and LeSage, 2011; Benos and Karagiannis, 2016; Tientao et al., 2016; Ugur et al., 2020). Public infrastructures in the transportation sector induce higher agglomeration, land value and accessibility (Cantos et al., 2005; Bronzini and Piselli, 2009; Yu et al., 2013; Januário et al., 2021). Conversely, for other investments sectors it is less evident the relevance of generated externalities.

Our work differs from previous studies, which consider spillovers generated by aggregate SCFs according to geographical distance (Brasili et al., 2012; Antunes et al., 2020; Cartone et al., 2021), since we model spatial weight matrices for specific sectors based on both physical distance and technological proximity, using state of the art approaches in line with Benos et al. (2015) and Fiaschi et al. (2018). We thus contribute to the current debate in which externalities based on simplistic weight matrices are criticized for providing inaccurate indications of interregional dependences (Pieńkowski and Berkowitz, 2016). To the best of our knowledge this is the first work assessing spillovers associated with SCFs deployed by investment sector according to different physical distance and technological proximity matrixes.

3 Data

3.1 The European Commission cross-section dataset

In the cross section analysis described in paragraph 4.1 we employ data on SCFs over the time frame 2007-2014 and we focus on 258 NUTS 2 regions, belonging to EU 27 countries, with the exclusion of Croatia as it joined EU in 2013.[4] Appendix A reports a detailed list of NUTS 2 regions included in our research.

Here, our main research purpose aims to understand whether the allocation of EU funds across different sectors generate heterogeneous economic growth rates. We focus on the following main sectors: *Energy*, *Environment*, *Human Resources*, *IT Infrastructures*, *Research and Development*, *Rural Development*, *Social Infrastructures*, *Tourism* and *Transportation*. These reference sectors are identified according to the industries reported in the Eurostat "Integrated database of allocations and expenditures".[5]

Table 1: Descriptive statistics of total SCFs expenditures per capita at NUTS 2 level across investments sectors over the period 2007-2014.

	Q1	Median	Q3	Std.Dev
SCF: Energy	1.207	5.932	21.938	65.981
SCF: Environment	1.503	9.613	94.415	130.624
SCF: Human Resources	0.000	0.011	1.557	4.588
SCF: IT Infrastructures	0.708	4.089	25.660	39.472
SCF: R&D	14.268	30.649	100.614	112.201
SCF: Rural Development	0.047	3.485	19.168	37.810
SCF: Social Infrastructures	0.000	0.133	41.056	82.246
SCF: Tourism	0.097	3.067	19.332	36.036
SCF: Transportation	0.005	6.329	219.187	353.092
SCF Concentration	0.152	0.210	0.285	0.107

Table 1 shows descriptive statistics of total SCFs expenditures per inhabitant across investment sectors disclosed by the EC in the period 2007-2014. Over the considered time frame, we find that the highest portions of the EU budget are devoted to the *Environment*, *R&D* and *Transportation* sectors, coherently with information disclosed by the EC in the ex-post evaluation of the corresponding programming period.[6] Conversely, the *Human Resources* sector

[4]We do not include in the analysis the oversea departments of France and the Spanish exclaves of Ceuta and Melilla since they are physically located in different continents and their development patterns might be affected by different factors.

[5]The database can be found at the link: `https://ec.europa.eu/regional_policy/it/policy/evaluations/data-for-research/`.

[6]See the EC document available at the following link: `https://ec.europa.eu/regional_policy/en/information/publications/evaluations/2016/`

receives the lowest portion of financial support.

3.2 The panel dataset

To the best of our knowledge, the EC provides data only on the total annual amount of SCFs expenditures at NUTS 2 level (*Aggregate SCF*) through the "Historic European Structural and Investment Funds" dataset[7], but there is no available information on how these values are disaggregated by investment sector.

For this reason we propose to reconstruct the annual SCFs expenditures for each sector k and region i as the product between the annual *Aggregate SCF* of region i and the annual share of EU SCFs allocated to sector k and region i in year t ($Percentage_{i,t,k}$) that we reconstruct from the EC portal. The amount of SCFs expenditures per inhabitant in region i, year t and sector k ($SCF_{i,t,k}$) is thus equal to:

$$SCFs_{i,t,k} = \frac{Aggregate\ SCF_{i,t} * Percentage_{i,t,k}}{Population_{i,t}} \tag{1}$$

where in order to estimate the term $Percentage_{i,t,k}$ we exploit the EC portal, which includes the main initiatives financed through SCFs in the programming periods 2000-2006, 2007-2013 and 2014-2020 and describes in aggregate the referring NUTS 2 regions and the corresponding sectors in which the transfers are spent. This dataset covers more than 100 billion euros corresponding to 26.1% of the overall EU budget, and constitutes a representative sample for the wide variety of initiatives financed across different sectors.[8]

More specifically, SCFs expenditures are directly allocated to a single region only in about 55% of the projects (*Region specific SCFs*) reported in the EC portal. Hence, for *Cross-regional SCFs*, we decide to adopt a methodology similar to Fiaschi et al. (2018) to approximate the amount of SCFs expenditures for each NUTS 2 region.[9] In particular, if the underlying project

commission-staff-working-document-ex-post-evaluation-of-the-erdf-and-cohesion-fund-2007-13. Despite the considered programming period is 2007-2013, the EC discloses the SCFs expenditures for the time frame 2007-2014 due to the N+2 rule, according to which SCFs can be spent up to two years after the conclusion of the underlying programming period.

[7]The EC Historic European Structural and Investment Funds dataset is available at the link: https://cohesiondata.ec.europa.eu/Other/Historic-EU-payments-regionalised-and-modelled/tc55-7ysv.

[8]For additional information, see also the document available at the following link: https://www.bruegel.org/2019/05/how-to-improve-european-union-cohesion-policy-for-the-next-decade/.

[9]We differ from Fiaschi et al. (2018) since they allocate cross regional projects in an amount inversely proportional to GDP per capita of NUTS 2 regions, while we allocate cross regional projects in an amount proportional to the surface area of the underlying NUTS 2 regions.

does not directly disclose the set of specific regions receiving the financial aid, but reports only the one or more countries that are the recipients of these SCFs, we distribute the financial support across the NUTS 2 regions of these countries in an amount proportional to the local surface area of each administrative unit. Furthermore, whenever cross-country projects explicitly target only Objective 1 regions, we restrict the allocation of SCFs to only the NUTS 2 regions officially admitted to benefit from the Objective 1 transfers, thus excluding those administrative units located in these countries but that are not eligible for this programme of financial support. Therefore, for each *cross-regional projects* j performed in year t in sector k, the amount of SCFs expenditures allocated to a region i involved in the project is equal to:

$$Cross\ regional\ SCF_{i,j,t,k} = Project\ SCF_{j,t,k} * \frac{Surface\ Area_i}{\sum_g Surface\ Area_g} \tag{2}$$

where $Project\ SCF_{j,t,k}$ are the overall cross-regional SCFs expenditures for project j performed in year t and in sector k, $Surface\ Area_i$ is the surface area of the underlying region i and $\sum_g Surface\ Area_g$ is the total surface area of all regions involved in the project.

Then, we estimate the annual share of EU transfers allocated to each sector k for every NUTS 2 region i ($Percentage_{i,t,k}$) as the ratio between the annual regional SCFs expenditures in each sector, that we have reconstructed as indicated above, and the corresponding total aggregate annual regional SCFs expenditures:

$$Percentage_{i,t,k} = \frac{Reconstructed\ SCF_{i,t,k}}{\sum_k Reconstructed\ SCF_{i,t,k}} \tag{3}$$

where $Reconstructed\ SCF_{i,t,k}$ is the total amount of SCFs expenditures in region i in year t in sector k, computed as the sum of $Region\ specific\ SCFs_{i,t,k}$ and $Cross\ regional\ SCFs_{i,t,k}$.

Based on SCFs$_{i,t,k}$ computed through Equation 1, we obtain the annual average SCFs expenditures during the period 2007-2014 across different sectors for each NUTS 2 that we employ in section 5.1. In this way, both the cross-section and panel analyses are based on the same aggregate amount of SCFs, increasing the comparability of the results.

In Appendix B, we perform some validation checks at different geographical scales based on the EC cross section dataset described in section 3.1 to ensure that our sample is representative and coherent with official data disclosed by European statistical offices.

4 Methods

4.1 Cross Section Analysis

We estimate an augmented β-convergence model with the following cross-section specification:

$$Y_i = \beta_0 + \beta_1 \log(Initial\ GDPpc_i) + \beta_2 Population\ Growth_i + \beta_3 Capital\ Formation_i + \beta_4 Schooling_i + \beta_5 SCF\ Concentration_i + \gamma_k \sum_k SCF_{k,i} + \delta_l \sum_l Employment_{l,i} + \epsilon_i \quad (4)$$

where indexes i, k and l denote the underlying NUTS 2 region, the sector in which SCF funds are spent and the industry of the local production structure, respectively. Table 2 reports the definitions and data sources for each variable used in Equation 4.

Table 2: Variables definitions and sources.

Variable Name	Definition	Source
Y_i	First difference of the natural logarithm of regional GDP per capita in PPS euros between two consecutive years, averaged over the period 2007-2014	ARDECO
Initial GDPpc	Natural logarithm of average regional GDP per capita over the programming period 2000-2006	ARDECO
Population Growth	First difference of the natural logarithm of resident population between two consecutive years, averaged over the period 2007-2014	ARDECO
Capital Formation	Investments in capital goods expressed as a percentage of regional GDP, averaged over the period 2007-2014	ARDECO
Schooling	Percentage of citizens with tertiary education among people between 35 and 64 years, averaged over the period 2007-2014	Eurostat
SCF	Yearly SCFs per capita spent by NUTS 2, averaged over the period 2007-2014	Author's calculation based on data on EC projects and EC SCFs
SCF Concentration	Sum of squared percentages of SCFs expenditures in each sector (HHI indicator)	Author's calculation based on data on EC projects and EC SCFs
Employment	Ratio between the number of employees in a sector and the overall number of employees in the region, averaged over the period 2007-2014	ARDECO

The dependent variable Y_i is the average over the time span 2007-2014 of yearly percentage variation in GDP per capita expressed in Purchasing Power Standard (PPS) currency and computed as the difference of natural logarithms of GDP per capita between two consecutive years.

Our main interest variable is constituted by regional expenditures of SCFs per capita disaggregated by the k investment sectors (namely, $\sum_k SCF_k$), computed as the yearly average of SCFs expenditures during the period 2007-2014 across different sectors. Moreover, since the diversification of the EU transfers might be an additional driver of economic development, we include the *SCF Concentration*, computed as the Herfindahl–Hirschman index[10] of the EU funds across sectors in each NUTS 2 region.

In order to assess the mechanism of convergence, we take into account the *Initial GDPpc*$_i$, which refers to the average GDP per capita of region i in the previous programming period (2000-2006), allowing us to analyze whether regions with pre-existing lower levels of income per capita subsequently experience higher economic growth rates than wealthier areas.

As control variables, we refer to those factors that may affect both regional disparities and SCFs expenditures, whose omission might bias therefore the estimated impact of $SCFs$. In accordance with the neoclassical growth model, we include the *Population Growth* rate, which under the hypothesis of full employment is expected to be a precise indicator of the variation in the number of local employees, capturing the dynamics in the evolution of the local labour market.

Moreover, we include *Capital Formation*, expressed as percentage of GDP at NUTS 2 level, to take into account the net capital accumulated within an accounting period and invested in capital goods, such as equipment, tools, transportation and electricity assets. Human capital endowment is a key determinant for reducing divergence across regions (Rodríguez-Pose and Vilalta-Bufí, 2005). Since the presence of a skilled manpower has a positive impact on the market labour productivity to account for heterogeneity in the education background of different regions, we include the share of tertiary schooling level citizens over the total population between 35 and 64 years (namely, *Schooling*).

Regional policy effectiveness is not neutral with respect to specific territorial assets char-

[10]We define the *SCF Concentration* in region i as $\sum_k \left[\frac{SCF_{k,i}}{Total\ SCF_i}\right]^2$, where $Total\ SCF_i$ is the sum of SCF_i received by region i across the different sectors.

acterizing the EU regions and, in particular, development patterns can change substantially depending on the local economic productive structure (Bachtrögler et al., 2020). For this reason, we include as controls the percentage of employment in different industries (according to NACE rev.2 classification) with respect to the local active population in the corresponding region (namely, *Employment*).

Table 3: Descriptive statistics of Dependent and Control variables.

	Q1	Median	Q3	Std.Dev
GDPpc growth	-0.001	0.017	0.054	0.036
Initial GDPpc	$14,589$	$23,378$	$27,622$	$10,786$
Capital Formation	0.191	0.217	0.234	0.039
Population Growth	-0.001	0.002	0.006	0.006
Schooling	0.170	0.242	0.307	0.111
Employment: A	0.015	0.029	0.058	0.070
Employment: B-E	0.103	0.136	0.189	0.063
Employment: F	0.057	0.065	0.071	0.014
Employment: G-J	0.205	0.236	0.267	0.056
Employment: K-N	0.088	0.119	0.154	0.060

Table 3 shows descriptive statistics of the dependent variable and controls used in the empirical analysis. Over the considered time frame, the analysed EU regions experience an overall positive economic raise, with an average and median GDP per capita growth equal to 2.0% and 1.7%, respectively. The most extreme values in the distribution of the dependent variable are assumed by NUTS 2 in new member states, such as Czech Republic, Polonia and Romania, subject to larger economic fluctuations (Alcidi, 2019; Andor, 2019).

4.2 Generalized Propensity Score Matching with Continuous Treatment

We investigate the causal impact of different SCFs expenditures intensities across sectors through a Generalized Propensity Score (GPS) Matching procedure, based on continuous treatment (Hirano and Imbens, 2004; Imai and Van Dyk, 2004). This approach contributes to reduce the selection bias among heterogeneous levels of treatment intensity by comparing regions that show similar observable characteristics.

Following Becker et al. (2012), who implemented this methodology in a similar analysis to identify the optimal allocation of SCFs, we assume that our treatment intensity, represented by

SCFs expenditures per capita given the covariates, follows a normal distribution:

$$SCF_i|X_i \sim N(\beta_0 + X_i\beta_1, \sigma^2) \tag{5}$$

where X_i is the vector of control variables outlined in section 4.1 and β_1 is a column vector of coefficients.

We estimate Equation 5 through OLS and building on this model we compute the GPS (R_i) as:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma^2}}}\exp(-\frac{1}{\hat{\sigma^2}}(SCF_i - \hat{\beta}_0 - X_i\hat{\beta}_1)^2) \tag{6}$$

Based on Becker et al. (2012), we use the GPS to restrict the analysis to more comparable groups and remove bias in the estimate of the causal impact of treatment intensity. We organize the data in four groups, discretizing the treatment intensity according to the quartiles of the distribution. In particular, for each treatment group $j \in \{1, 2, 3, 4\}$ we calculate the median treatment intensity SCF_M^j and for each region we compute the GPS in correspondence of the median treatment intensity $R_i(SCF_M^j,\ X_i)$ according to Equation 6. Then, we keep for the analysis only those observations l that respect the following common support condition:

$$Quantile\{\hat{R}_s(SCF_M^j, X_s), 0.2\} \leq \hat{R}_l(SCF_M^j, X_l) \leq Quantile\{\hat{R}_s(SCF_M^j, X_s), 0.8\}\ \forall j \in \{1, 2, 3, 4\} \tag{7}$$

where $s \in j$, $l \notin j$ and $Quantile\{\hat{R}_s(SCF_M^j, X_s), 0.2\}$ and $Quantile\{\hat{R}_s(SCF_M^j, X_s), 0.8\}$ are the 0.2 and 0.8 quantiles of $R_s(SCF_M^j,\ X_s)$, respectively. In this way, we require that analysed observations display a sufficient degree of similarity in the observable characteristics determining treatment intensity. Then, for each sector we estimate the interplay between regional SCFs expenditures intensity and GDP per capita growth. More specifically, for each investment sector k we estimate the following OLS model:

$$Y_i = \alpha_0 + \alpha_1 SCF_{i,k} + \alpha_2 SCF_{i,k}^2 + \beta_1\hat{R}_{i,k} + \beta_2\hat{R}_{i,k}^2 + \gamma X_i + \epsilon_i \tag{8}$$

where Y_i is GDP per capita growth in region i, $SCF_{i,k}$ is the expenditures intensity per capita in region i and sector k, $\hat{R}_{i,k}$ is the GPS for region i for investment sector k and X_i is the matrix of controls described in section 4.1. In this case, α_1 and α_2 represent our coefficients of interest, as they summarize the relationship between treatment intensity and local economic growth among comparable units.

4.3 Panel Analysis

SCFs expenditures in different sectors might require time before generating significant effects on local development. For this reason, we propose to estimate also the following panel specification, where we investigate the impact of SCFs expenditures on regional economic growth at different time lags:

$$\begin{aligned} Y_{i,t} = \beta_0 + \beta_1 \log(GDPpc_{i,t-1}) + \beta_2 Population\ Growth_{i,t} + \beta_3 Capital\ Formation_{i,t} + \\ \beta_4 Schooling_{i,t} + \beta_5 SCF\ Concentration_{i,t-j} + \delta_l \sum_l Employment_{l,i,t} + \\ \gamma_k \sum_k SCF_{k,i,t-j} + \epsilon_i + u_{i,t} \end{aligned} \tag{9}$$

We estimate a different model for each time lag $t-j$ with $j \in \{0, 1, 2, 3, 4, 5\}$, thus analysing both immediate effects generated by current SCFs expenditures and medium-long term effects produced after a time span between 1 and 5 years from the SCFs expenditures. In this case, the annual amount of regional SCFs expenditures in each sector ($\sum_k SCF_{k,i,t}$) is computed as described in section 3.2.

4.4 Spatial dependence and externalities across regions

Externalities arise due to the combination of mechanisms contributing to economic growth, such as physical proximity, technological specialization and labor mobility. For this reason, we model a set of different weight matrices in order to properly account for the potential factors that might generate spillovers.

First, we model traditional weight matrices based on the great circle distance between the centroids of different regions. Based on the application of the K-Nearest Neighbours (KNN) algorithm, we thus define this spatial matrix $\mathbf{W}$ as:

$$\mathbf{W} = \begin{cases} w^*_{i,j} = 0 & \text{if } i = j \\ w^*_{i,j}(k) = 1 & \text{if } d_{i,j}(k) \leq d_i(k) \quad and \quad w_{i,j} = \frac{w^*_{i,j}(k)}{\sum_j w^*_{i,j}(k)} \\ w^*_{i,j} = 0 & \text{if } d_{i,j}(k) > d_i(k) \end{cases}$$

where $d_i(k)$ is the cutoff threshold, representing the distance of the k^{th} closest region to NUTS 2 region i, such that each administrative unit has exactly k neighbours. Following Ertur and Koch (2006), we set $k = 10$. Hence, w^*_{ij} is an element of the unstandardized weight matrix $\mathbf{W}$, while $w_{i,j}$ is an element of the standardized weight matrix in which the sum of each element of a row equals to 1.

Then, we consider three alternative row standardized weight matrices defined as a function of the technological similarity $s_{i,j}$:

$$\mathbf{W} = \begin{cases} w^*_{i,j} = 0 & \text{if } i = j \\ w^*_{i,j} = s_{i,j} & \text{if } i \neq j \quad and \quad w_{i,j} = \frac{w^*_{i,j}}{\sum_j w^*_{i,j}} \end{cases}$$

In the first case, we model the similarity across NUTS 2 regions based on the relative magnitude of the respective GDP per capita. In particular, following Benos et al. (2015) we define $s_{i,j} = 1 - |\overline{GDPpc_i} - \overline{GDPpc_j}|/|\overline{GDPpc_i} + \overline{GDPpc_j}|$, where $\overline{GDPpc_i}$ is the average GDP per capita of region i over the analysed time frame. Therefore, similarity among NUTS 2 regions is based on the economic characteristics and each region is not forced to have exactly $k-$fixed neighbours. Similarity is equal to 1 in case two regions have exactly the same GDP per capita and it progressively vanishes as the difference in GDP per capita increases.

Then, we consider a matrix based on the similarity of the share of GDP generated across different sectors. More precisely, in this case we define $s_{i,j} = 1 - 0.5 \sum_s |p_{s,i} - p_{s,j}|$, where $p_{s,i}$ is the percentage of GDP generated in sector s by region i. With this approach, we adopt the similarity measure introduced by Bray and Curtis (1957) and exploited, for instance, by De Benedictis and Tajoli (2007) to measure the economic integration in trade structures and by Fiaschi et al. (2018) to evaluate spillovers generated by SCFs. This approach progressively increases the complexity of how spatial relationships are modelled since we do not consider proximity based only on the similarity of the overall GDP per capita, but instead we disaggregate it with respect to the local production structure and sectors.

Finally, we take into consideration a matrix based on the similarity of the share of patents generated within sectors. We follow the same definition used for the previous matrix, with the difference that in this case $p_{s,i}$ is the percentage of patents generated in sector s by region i. A similar approach was adopted by Basile et al. (2012) and Marrocu et al. (2013) to assess knowledge spillovers in Europe from R&D expenditures. The matrix based on GDP by sector accounts for similarity in the local production structure, while the variant computed on patents allows us to model similar potential trends of future development for these regions.

We analyse the relevance of externalities generated by SCFs relying on a Spatial Durbin Model (SDM). By means of the spatial autoregressive component ($WY_{i,t}$), we are thus able to model the fact that a variation in the GDP per capita growth of a region can induce a variation in the same variable of a geographically close or technologically similar region. Moreover, through the spatial exogenous component ($\theta_k W \sum_k SCF_{k,i,t}$), we model how a variation in the amount of SCFs expenditures in region i in sector k can affect the GDP per capita growth of other geographically close or technologically similar regions. In formula:

$$\begin{aligned}Y_{i,t} = \lambda WY_{i,t} + \beta_0 + \beta_1 \ \log(GDPpc_{i,t-1}) + \beta_2 \ Population\ Growth_{i,t} + \beta_3 \ Capital\ Formation_{i,t} \\ +\beta_4 Schooling_{i,t} + \beta_5 \ SCF\ Concentration_{i,t} + \delta_l \sum_l Employment_{l,i,t} + \gamma_k \sum_k SCF_{k,i,t} \\ +\theta_k W \sum_k SCF_{k,i,t} + \epsilon_i + u_{i,t} \qquad (10)\end{aligned}$$

Based on Equation 10, by adopting a terminology similar to the one used by LeSage (2008) and Elhorst (2014) we define direct, indirect and total effects as follows:[11]

$$\begin{pmatrix} \partial E(Y_1)/\partial SCF_{1,k} & \dots & \partial E(Y_1)/\partial SCF_{n,k} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \partial E(Y_n)/\partial SCF_{1,k} & \dots & \partial E(Y_n)/\partial SCF_{n,k} \end{pmatrix} = (\mathrm{I}\text{-}\lambda \mathrm{W})^{-1} \ [\gamma_k \mathrm{I}_n \ + \vartheta_k \ \mathrm{W}] = \mathrm{Sr(W)}$$

$$Direct\ Effects = \frac{1}{N} trace(Sr(W))$$

[11] With the term $\partial E(Y_i)/\partial SCF_{j,k}$, we model the variation of GDP per capita growth in region i due to a variation of SCFs in region j and sector k.

$$Total\ Effects = \frac{1}{N}\sum_i \sum_j Sr(W)_{i,j}$$

$$Indirect\ Effects = Total\ Effects - Direct\ Effects$$

To test the statistically significance of the direct and indirect effects, we rely on the procedure derived by Elhorst (2014) for panel models. In particular, we sample sets of observations from the distribution of parameters and compute for each of them direct and indirect effects. In this way, we can obtain a distribution of direct and indirect effects and then, based on such empirical values, it is possible to perform a t-test to assess their significance. More precisely, one particular combination drawn (d) of parameters is equal to the sum between the point estimates of the parameters and a random component obtained as the product between the upper-triangular Cholesky decomposition of the variance–covariance matrix of the parameters (P) and the vector (ϕ) of length equal to the number of parameters and sampled from a normal distribution with zero mean and variance one. In formula:

$$[\lambda_d, \gamma_{k,d}, \theta_{k,d}] = P^T\phi + [\lambda, \beta_1, \beta_2, ...] \tag{11}$$

We consider 1,000 draws (d) of parameters λ_d, $\gamma_{k,d}$, $\theta_{k,d}$ and for each draw we compute the corresponding direct and indirect effects.

5 Empirical analysis

Section 5.1 and 5.2 analyse the immediate effects generated by SCFs in different sectors. Section 5.3 discusses medium-short term impacts of EU transfers, while section 5.4 investigates geographical and technological spillovers across sectors in EU regions.

5.1 The role of sectors

As shown in Table 4 (models 1-3), we identify positive effects for SCFs in *Human Resources*, corroborating the fact that expenditures in training, education and other activities related to the improvement of skills constitute a key driver for local development (RodrÍguez-Pose and Fratesi, 2004).

As regards SCFs into the *R&D* sector, we find a positive coefficient, coherently with a large stream of literature that documented a positive relationship between investments in R&D activities and GDP per capita growth (Prettner and Werner, 2016). Similar results have been recently obtained also by Gumus and Celikay (2015), who provided supporting evidence that this type of investment contributes to technological breakthroughs that represent endogenous determinants of economic growth. Indeed, R&D expenditures stimulate innovation, new knowledge and the development of more efficient production and service processes, leading to higher levels of income and growth (Männasoo et al., 2018).

In addition, a positive and significant coefficient is associated with SCFs in the *Transportation* sector. This result is relevant considering that it accounts for 38% of the overall EU budget. Our results provide indications that over the analysed period this type of expenditures generated positive benefits. Improved market accessibility, enhanced competition, increased land value and higher chances of clustering thus seem to compensate potential negative externalities associated to congestion and urban crowding (Puga, 2008; Venables et al., 2021).

These positive effects are coherent with the neoclassical growth theory, suggesting human capital, infrastructures (Solow, 1956) and technology (Romer, 1990) as main drivers of local development. Moreover, they are consistent with other studies focusing on the impact of the EU Cohesion Policy in specific development axis, showing how R&D, infrastructures and human capital investments represent relevant drivers of income and economic output growth in a medium-long term run (Bronzini and Piselli, 2009; Varga and Veld, 2011). For instance, Bachtler et al. (2013) discuss how the R&D sector has progressively increased its relevance within the EU Cohesion policy across different programming periods, boosting research activities and the innovation rate of regions and leading to a higher economic growth. As an example, they found that Ireland in 2010 reached a high level of R&D investments in the public and private sectors (equal to 2.21% with respect to the Gross National Product), experiencing an average GDP per capita growth rate equal to 2.2% in the following five years.

Similarly, basic hard infrastructures are found to represent necessary conditions to promote local development, contributing to an improvement of accessibility, agglomeration, birth of new business activities and jobs creation (Gibbons et al., 2019; Cascetta et al., 2020). Aschauer (1989) showed that investments in core transport infrastructures have the highest impact on productivity growth. The positive effect of this type of expenditures has been recently confirmed by Lee (2021) who explain how investments in road infrastructures increase local accessibility leading to a higher firms productivity. Furthermore, Petráš and Květoň (2020) highlight how a higher proximity to motorways can foster firms birth. In addition to this, our results on transport infrastructure investments can be justified also by the fact that this type of public expenditures tends to be counter-cyclical, thus displaying a higher economic multiplier thanks to their capability to crowd-in private investments and stimulate firms investment confidence in periods of high uncertainty (Auerbach and Gorodnichenko, 2012; Auerbach et al., 2012; Candelon and Lieb, 2013; Canzoneri et al., 2016).

Finally, investments for the development of human capital may lead to more skilled local employees activating a positive mechanism of higher firms productivity and larger innovation rates representing key drivers of economic growth (Teixeira and Queirós, 2016; Lenihan et al., 2019).

By contrast, SCFs in the *Environment* sector reveal a not significant or even negative effect depending on model specification. This is extremely relevant due to the pivotal role that expenditures in this sector account for long term policies. Indeed, the European Green Deal, stating that EU should become a neutral climate area by 2050, with zero net carbon emissions, will promote initiatives for the realization of environmentally-friendly technologies, cleaner and healthier forms of public and private transport and more efficient energy systems. In this direction, the EU displaced the "Just Transition Mechanism", mobilising more than 100 billion euros for the programming period 2021-2027 to provide financial support and technical assistance for this green revolution. Hence, it is critically relevant to highlight low economic performances associated with investments in the environmental sector, contributing to the current debate between long term sustainable development and economic growth.

Finally, funds allocated to the other sectors, such as *Energy, IT Infrastructures, Rural development*, *Social Infrastructures* and *Tourism*, do not show statistically significant effects.

Interestingly, we find a negative and statistically significant coefficient for *SCFs Concentration*, suggesting that more diversified transfers are more effective to promote regional growth. This is coherent with the idea of complementary expenditures that display higher returns in case they finance assets that the local business environment lacks (Duranton and Venables, 2018). This finding fuels the discussion on whether SCFs should target specific single sectors, trying to be complementary to local policies of economic support already in place in the financed regions, or if instead they should constitute an instrument directly pursuing the support of a heterogeneous set of initiatives across different sectors.

Although the design of complementary policy packages of financial support might be complex, since interactions among sectors might be not obvious, our findings suggest that over the period 2007-2014 administrative units exposed to more diversified funds experienced on average higher economic results. This pattern highlights that the level of diversification should be considered as a relevant determinant to explain competing GDP per capita growth patterns among EU regions, complementing previous studies which almost neglected this dimension. Indeed, more comprehensive investment strategies can activate mechanisms of coordinated movement, reducing the risk of misaligned development across industries, market failures and not optimal conditions for integrated growth (Duranton and Venables, 2018). As a consequence, our results suggest that policy makers should explicitly take into account the level of complementarity in the SCFs allocated to NUTS 2 regions due to its potential in affecting economic development.

As for the control variables, we find the expected signs, coherently with the neoclassical growth theory. Indeed, all the three estimated models provide significant evidence of convergence, as the coefficient of *Initial GDPpc* is negative, suggesting that poorer areas tend to catch up with wealthier regions. More precisely, we identify a rate of convergence[12] between 5.6% and 7.6% (models 1-3). This value for the convergence rate is higher than those estimated for previous periods, where extant literature found evidence for a rate of convergence around 2% (Sala-i Martin, 1996). However, higher convergence rates after the entrance of ten countries in the EU as of 1^{st} May 2004 were found also by other studies (Próchniak and Witkowski, 2013; Goedemé and Collado, 2016). This is due to the larger economic growth rates experienced by the new member states characterized by significantly lower levels of GDP with respect to EU-15 NUTS 2. In addition, our estimates are in line with those of Alcidi (2019) and Andor (2019), who found evidence of two clusters in terms of GDP increase, with new EU countries outperforming EU-15 members.

Population Growth, *Capital Formation* and *Schooling* coefficients are not statistically significant, as in Dall'Erba and Le Gallo (2008), Mohl and Hagen (2010) and Pinho et al. (2015).

As robustness, we repeat the same analysis (models 4-6) introducing fixed effects and clus-

[12] The β-convergence model can be written as: $\log Y_{i,t} - \log Y_{i,t-1} = \beta_0 - (1 - e^{-\lambda t}) \log Y_{i,t-1}$ where λ represents the rate of convergence. In the absolute convergence model rewritten as: $\log Y_{i,t} - \log Y_{i,t-1} = \beta_0 + \beta_1 \log Y_{i,t-1}$, it is possible to obtain $\lambda = \frac{-\log(1+\beta_1)}{\tau}$, where τ represents the length of one time period.

Table 4: OLS regression model with White heteroskedasticity robust standard errors. In Columns 4-6 we show the results introducing country fixed effects and clustered standard errors at national level. Standard errors are reported in parentheses.

	Dependent variable:					
	GDPpc growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.000	−0.000	−0.000	−0.378	−0.293	0.129
	(0.046)	(0.046)	(0.044)	(0.245)	(0.255)	(0.282)
Initial GDPpc	−0.054***	−0.054***	−0.073***	−0.055***	−0.053**	−0.114***
	(0.004)	(0.006)	(0.008)	(0.019)	(0.025)	(0.037)
Energy	0.025	0.027	0.069	0.121	0.111	0.209**
	(0.087)	(0.090)	(0.092)	(0.101)	(0.099)	(0.091)
Environment	−0.145***	−0.137**	−0.094	−0.084	−0.082	−0.098
	(0.052)	(0.064)	(0.059)	(0.069)	(0.086)	(0.084)
Human Resources	0.162**	0.157**	0.145**	0.306***	0.292***	0.291***
	(0.069)	(0.070)	(0.069)	(0.089)	(0.090)	(0.076)
IT Infrastructures	−0.020	−0.021	−0.006	0.053	0.054	0.040
	(0.052)	(0.053)	(0.048)	(0.056)	(0.056)	(0.048)
R&D	0.107*	0.102	0.116*	0.125**	0.097	0.124**
	(0.062)	(0.062)	(0.063)	(0.060)	(0.060)	(0.057)
Rural Development	−0.041	−0.037	−0.073	−0.004	0.017	0.012
	(0.087)	(0.090)	(0.081)	(0.094)	(0.099)	(0.091)
Social Infrastructures	−0.027	−0.041	−0.069	−0.084	−0.067	−0.037
	(0.092)	(0.096)	(0.100)	(0.105)	(0.107)	(0.105)
Tourism	−0.035	−0.030	−0.049	−0.196	−0.182	−0.187
	(0.063)	(0.064)	(0.061)	(0.173)	(0.175)	(0.172)
Transport	0.165*	0.172*	0.205**	0.193*	0.208*	0.180*
	(0.098)	(0.102)	(0.092)	(0.113)	(0.121)	(0.108)
SCF Concentration	−0.110*	−0.115*	−0.123*	−0.137*	−0.135*	−0.142*
	(0.065)	(0.067)	(0.066)	(0.078)	(0.077)	(0.076)
Capital Formation		−0.038	−0.046		−0.047	−0.035
		(0.059)	(0.053)		(0.070)	(0.065)
Population Growth		−0.012	−0.112*		0.057	−0.022
		(0.061)	(0.061)		(0.085)	(0.081)
Schooling		−0.003	0.083		0.111	0.078
		(0.058)	(0.063)		(0.160)	(0.151)
Employment A			−0.183***			−0.327***
			(0.065)			(0.077)
Employment B-E			−0.028			−0.106
			(0.060)			(0.085)
Employment F			0.111**			0.125**
			(0.050)			(0.057)
Employment G-J			−0.140*			−0.214**
			(0.072)			(0.097)
Employment K-N			0.281***			0.427***
			(0.089)			(0.135)
Observations	258	258	258	258	258	258
R^2	0.453	0.454	0.504	0.513	0.516	0.573
Adjusted R^2	0.428	0.423	0.464	0.431	0.427	0.482
Note:						*p<0.1; **p<0.05; ***p<0.01

tered standard errors at national level to ensure that our results are not driven by specific patterns occurring in some specific EU countries. Overall, we obtain similar results across sectors. However, the *Energy* sector displays a higher magnitude and statistical significance, possibly due to the fact this type of expenditure may contribute to reduce fixed production costs and enhance productivity (Salim et al., 2014). Conversely, the Environment sector is still characterized by a negative coefficient, but in this case it is not statistically significant.

5.2 The casual impact of sector investments

OLS estimates of section 5.1 might be biased since the most significant portion of SCFs is allocated to Objective 1 areas, which are lagging regions with a GDP per capita lower than 75% of the EU average. In addition, the intensity of received funds is proportional to the development gap with respect to wealthier areas. Consequently, the EU funds might be an endogenous dimension.

To explicitly deal with this problem previous works exploited lags of EU transfers as potential instruments through the application of the GMM estimator (Esposti and Bussoletti, 2008; Mohl and Hagen, 2010). Alternatively, other studies relied on the three groups method developed by Kennedy (2008), where the instrumental variables for the SCFs take on values -1, 0, or 1 if the potentially endogenous regressor is, respectively, in the bottom, middle, or top third of its ranking, as recently employed also in Fiaschi et al. (2018). Finally, Dall'Erba and Le Gallo (2008) adopted the distances or time to travel of each region from Brussels as instrumental variables.

However, these strategies do not completely eliminate the endogeneity concern. Indeed, the exploitation of lagging independent variables is based on the untestable assumption of no dynamics among unobservables (Bellemare et al., 2017). The three group method may reduce endogeneity from measurement error, but cannot address omitted variables bias or reverse causality issues. Moreover, the distances or time to travel do not represent adequate instruments due to the EU enlargement in 2004, as new member states significantly affected the geographical distribution and concentration of EU funds.

For these reasons, in this section we show the results of a GPSM with continuous treatment, through which we aim to analyse the causal impact of SCFs expenditures across different sectors among comparable regions. The t-tests shown in Appendix C confirm that for SCFs in each sector we are able to restrict the analysis to NUTS 2 regions with comparable observable characteristics, with only few exceptions.

We find that both the SCFs expenditures in the *Energy* and *Transportation* sectors are characterized by a quadratic relationship with GDP per capita growth (see Table 5). This suggests that there exists a U-shaped reversed relationship between the two variables, meaning that an increase in the amount of EU transfers spent in these sectors generate a progressively higher contribution to the local economic growth up to a certain optimal expenditure intensity, above which the contribution to regional development is reduced. This is coherent with results obtained by Becker et al. (2012), who identify an optimal transfer intensity for SCFs around 1.2% with respect to the GDP of NUTS 2 regions.

We observe instead a linear relationship between SCFs expenditures in the *R&D* sector and GDP per capita growth, meaning that a growth in the amount of funds spent in this sector is associated with additional local development. On the other hand, we confirm that for the *Environment*, *IT infrastructure*, *Rural Development* and *Tourism* sectors there are not significant relationships between the expenditure intensity and the local economic growth, corroborating the results of section 5.1. Finally, we cannot estimate the results for the *Human Resources* and *Social Infrastructures* sectors due to the absence of enough NUTS 2 regions respecting the common support condition (see Equation 7). Although the GPSM procedure helps a better extraction of causal relationships, it comes at the cost of a decreased number of observations which may limit a proper statistical inference. Still, estimates reported in this section confirm the main findings discussed in section 5.1, highlighting heterogeneous impacts of SCFs expenditures across sectors.

Table 5: OLS estimates of Equation 8 with White heteroskedasticity robust standard errors. Standard errors are reported in parentheses.

	Dependent variable:						
	GDPpc growth						
	(Energy)	(Environment)	(IT Infr.)	(R&D)	(Rural Dev.)	(Tourism)	(Transp.)
Constant	−0.000 (0.080)	−0.000 (0.088)	−0.000 (0.089)	0.000 (0.084)	0.000 (0.083)	0.000 (0.097)	−0.000 (0.083)
SCF	0.393*** (0.147)	−0.074 (0.289)	0.105 (0.162)	0.381** (0.179)	0.016 (0.086)	0.137 (0.298)	0.820*** (0.148)
SCF^2	−0.236** (0.117)	−0.170 (0.180)	−0.152 (0.127)	−0.114 (0.125)	0.095 (0.073)	0.015 (0.233)	−0.222** (0.103)
GPS	−7.779*** (2.486)	−1.029 (1.002)	−0.270 (1.217)	2.793 (2.539)	−1.075 (0.719)	0.428 (0.498)	1.344 (1.501)
GPS^2	7.871*** (2.484)	1.228 (1.042)	0.397 (1.281)	−3.035 (2.542)	1.162 (0.771)	−0.368 (0.524)	−1.564 (1.568)
Initial GDPpc	−0.441** (0.195)	−0.401 (0.284)	−0.792*** (0.203)	−0.648*** (0.183)	−0.826*** (0.168)	−0.432** (0.198)	−0.109 (0.281)
Capital Formation	0.200 (0.120)	−0.131 (0.115)	−0.216* (0.125)	−0.084 (0.119)	−0.070 (0.111)	0.085 (0.119)	−0.093 (0.115)
Population Growth	−0.029 (0.113)	−0.522*** (0.178)	−0.258** (0.111)	−0.078 (0.125)	−0.177 (0.117)	−0.032 (0.150)	−0.428*** (0.131)
Schooling	−0.119 (0.108)	−0.125 (0.159)	0.001 (0.100)	0.046 (0.109)	0.017 (0.106)	−0.042 (0.127)	−0.068 (0.079)
Employment: A	0.109 (0.091)	0.522** (0.247)	0.210** (0.097)	0.404*** (0.107)	0.299*** (0.071)	0.345** (0.165)	−0.042 (0.090)
Employment: B-E	0.082 (0.099)	−0.065 (0.129)	0.159 (0.103)	0.121 (0.121)	0.083 (0.106)	0.286** (0.143)	−0.136 (0.134)
Employment: F	−0.209 (0.140)	0.147 (0.126)	−0.036 (0.115)	0.026 (0.097)	0.064 (0.088)	−0.020 (0.138)	0.140 (0.100)
Employment: G-J	−0.284** (0.120)	−0.267* (0.154)	−0.165 (0.129)	−0.286* (0.162)	−0.154 (0.160)	−0.325* (0.171)	−0.411*** (0.128)
Employment: K-N	0.136 (0.176)	0.375** (0.159)	−0.121 (0.136)	0.269 (0.192)	0.118 (0.142)	0.386** (0.175)	0.445*** (0.156)
Observations	79	66	70	94	112	70	57
R^2	0.493	0.487	0.439	0.335	0.224	0.329	0.598
Adjusted R^2	0.401	0.371	0.321	0.236	0.130	0.188	0.488
Note:							*p<0.1; **p<0.05; ***p<0.01

5.3 The role of sectors at different time lags

This section investigates the impact of SCFs expenditures across investment sectors at different time lags. To do this, we estimate a set of panel models with fixed effects and White heteroskedasticity robust standard errors.[13] We recognize an immediate effect of SCFs expenditures, which is coherent with the results obtained in the cross-section analysis of sections 5.1 and 5.2. Indeed, we confirm that EU transfers spent in the *Energy*, *Human Resources*, *R&D* and *Transportation* sectors have a positive and significant impact on regional GDP per capita growth (see Table 6).

We observe that SCFs in the *Transportation* sector induce positive and significant effects also at all time lags between 1 and 5 years, suggesting that this type of expenditure contributes

[13]We estimate two ways fixed effects panel models including fixed effects with respect to NUTS 2 regions and analysed years.

to substantial changes in the local infrastructure system with persistent long term benefits. Also the *Energy* sector is characterized by positive and statistically significant coefficients over the analysed period, with the exception of lag 3. Similarly, a positive medium-long term impact on regional economic growth is experienced by *R&D* expenditures, as the development of innovative business solutions and new technologies might require time before producing tangible economic advantages. Instead, we find that *IT Infrastructures* weakly contribute to GDP per capita growth with some time lags with respect to the real investment, since the main benefits are related to the exploitation of new infrastructures that allow faster connection systems, while the years immediately after the SCFs expenditures are characterized by the construction phase of telecommunication infrastructures.

Moreover, positive impacts on local development at different time lags are associated also with the *Rural Development* and *Tourism* sectors. This result is different from previous evidence obtained by Rodríguez-Pose and Fratesi (2004) who show how EU transfers in these sectors do not have long time impact on economic growth. However, this result is consistent with the fact that former EAGFF was replaced in 2006 by the EAFRD and EAGF, becoming part of a strategy to stimulate persistent economic growth in rural areas rather than being just an instrument to remunerate farmers for their role in preserving the rural heritage and extracting immediate value from the agriculture environment. Moreover, Rodríguez-Pose and Fratesi (2004) mixed SCFs expenditures for tourism with those for business support, thus preventing the possibility to disentangle the specific impact of each sector. Conversely, we show that over the time frame 2007-2014 the *Tourism* sector, receiving more than 8 billion € to finance infrastructures development, cultural heritage preservation, the organization of international events and the construction of business and accommodation facilities, contributed in the medium-term to regional GDP per capita growth in Europe (Haller et al., 2021).

Interestingly, note how the negative immediate effect associated with *Environment* expenditures is instead reversed by the positive impact at all time lags between 1 and 5 with the exception of lag 4, suggesting that this type of investment contributes to generate a more sustainable economic system in a medium-term perspective. Mixed effects are also observed for SCFs on *Human Resources*, although weakly statistically significant.

Finally, Table 6 confirms that a higher *diversification* of SCFs expenditures contributes to local development also in the medium-term. Coordination and integration of complementary investments across different sectors may thus require some years to generate a coherent development of the overall local business environment.

Table 6: Estimates of panel models with two ways fixed effects and White heteroskedasticity robust standard errors. SCFs expenditures by sectors are computed as described in section 3.2. Standard errors are reported in parentheses.

	Dependent variable:					
	GDPpc growth					
	(lag-0)	(lag-1)	(lag-2)	(lag-3)	(lag-4)	(lag-5)
GDPpc year before	-2.915^{***}	-2.970^{***}	-3.599^{***}	-4.251^{***}	-5.386^{***}	-7.304^{***}
	(0.172)	(0.192)	(0.207)	(0.214)	(0.382)	(0.639)
Energy	0.112^{***}	0.089^{***}	0.052^{*}	0.045	0.056^{*}	0.084^{**}
	(0.026)	(0.029)	(0.030)	(0.027)	(0.033)	(0.042)
Environment	-0.080^{***}	0.079^{**}	0.116^{***}	0.068^{*}	0.070	0.177^{***}
	(0.030)	(0.033)	(0.036)	(0.036)	(0.046)	(0.058)
Human Resources	0.050^{*}	-0.050	0.022	0.063^{*}	-0.109^{**}	-0.096
	(0.028)	(0.031)	(0.033)	(0.036)	(0.051)	(0.065)
IT Infrastructures	0.019	0.044	0.015	-0.017	0.063	0.118^{*}
	(0.029)	(0.031)	(0.034)	(0.033)	(0.042)	(0.061)
R&D	0.085^{***}	0.077^{***}	0.098^{***}	0.124^{***}	0.013	0.052
	(0.025)	(0.027)	(0.028)	(0.028)	(0.033)	(0.037)
Rural Development	0.014	0.084^{***}	0.085^{***}	0.019	0.017	0.095^{*}
	(0.024)	(0.026)	(0.033)	(0.032)	(0.038)	(0.053)
Social Infrastructures	-0.027	0.051	0.040	0.046	0.069	-0.059
	(0.032)	(0.033)	(0.035)	(0.036)	(0.050)	(0.060)
Tourism	-0.043	0.021	0.136^{***}	-0.011	0.078^{**}	-0.013
	(0.028)	(0.031)	(0.031)	(0.030)	(0.034)	(0.044)
Transportation	0.154^{***}	0.152^{***}	0.232^{***}	0.125^{***}	0.141^{***}	0.282^{***}
	(0.031)	(0.032)	(0.033)	(0.033)	(0.038)	(0.049)
SCF Concentration	-0.071^{***}	0.039	0.001	-0.062^{**}	-0.062^{*}	0.041
	(0.025)	(0.027)	(0.028)	(0.027)	(0.034)	(0.040)
Observations	2,064	1,806	1,548	1,290	1,032	774
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.262	0.284	0.420	0.363	0.335	0.384
Adjusted R^2	0.148	0.155	0.294	0.189	0.092	0.043
Note:						*p<0.1; **p<0.05; ***p<0.01

5.4 Geographical and Technological Spillovers: Direct and Indirect Effects

In this section, we analyze the spillovers generated by SCFs expenditures, as described in section 4.4.

Table D1 in Appendix D shows the results of SDMs estimated with different weight matrices. We find a positive and significant coefficient for the spatial autoregressive coefficient λ, with coefficients ranging between 0.92 and 1.25. This points to the presence of positive spillovers across regions characterized by physical proximity or technological similarity. The geographical spatial coefficient is in line with other previous studies in this field (Dall'Erba and Le Gallo, 2008; Ramajo et al., 2008; Mohl and Hagen, 2010). The estimates on technological matrices are consistent with those of Fiaschi et al. (2018) and contribute to the debate on the relevance of technological collaboration networks in regional contexts that accelerate synergies and similar patterns of economic development (Scherngell, 2021). The larger coefficient in technological rather than physical spatial matrices suggests that if in the past industrial clusters were constituted by geographical concentrations of interconnected firms, service providers and suppliers competing and cooperating in a specific market, nowadays similarity of local industrial and technological structures are relevant drivers for the formation of districts subject to interrelated GDP per capita variations (Cruz and Teixeira, 2010).

Table 7 reports the estimates of direct, indirect and total effects based on the coefficients of the SDM, with the weight matrix modelling geographical distances based on the estimation reported in Table D1.[14] We find that the *Energy* sector has positive significant direct and indirect effects, showing how this type of funding intervention affects not only the specific region where investments are made, but also neighbour administrative units, thereby generating positive externalities.

Table 7: Spatial Spillovers for EU funds under the geographical proximity specification for the weight matrix. Standard errors are reported in parentheses.

	Direct Effects	Indirect Effects	Total Effects
Energy	0.142***	1.767***	1.909***
	(0.025)	(0.520)	(0.543)
Environment	−0.023	-1.251**	−1.274**
	(0.029)	(0.611)	(0.638)
Human Resources	0.070***	0.841**	0.910**
	(0.025)	(0.417)	(0.440)
IT Infrastructures	0.033	0.279	0.313
	(0.032)	(0.665)	(0.695)
R&D	0.132***	1.567***	1.699***
	(0.024)	(0.502)	(0.524)
Rural Development	0.070***	1.007***	1.077***
	(0.020)	(0.340)	(0.358)
Social Infrastructures	0.018	−0.159	-0.141
	(0.029)	(0.524)	(0.551)
Tourism	−0.017	−0.545	-0.562
	(0.029)	(0.574)	(0.601)
Transportation	0.216***	2.961***	3.177***
	(0.034)	(0.787)	(0.817)

Note: *p<0.1; **p<0.05; ***p<0.01

[14] Similar results are obtained even for technological similarity matrices (see Tables D2, D3, D4 in the Appendix).

Moreover, we find positive direct and indirect effects for expenditures in *Human Resources*. This pattern suggests that an improvement in the human stock of one region might increase business competitiveness and productivity also of neighbour regions, due to labour mobility and knowledge spillovers (Benos and Karagiannis, 2016; Tientao et al., 2016). This is particularly relevant as *Human Resources* is the sector receiving the lowest portion of funds in the EU budget. Many studies revealed that the absence of adequately educated and skilled human stock is one of the key reasons for low levels of GDP per capita growth and absence of convergence in certain EU regions. Our findings suggest that policy maker might take into consideration also the emergence of such spillovers when allocating resources to this sector.

Similarly, direct impacts are strengthened by positive indirect effects also for *R&D*. This confirms the relevance of innovation and knowledge spillovers since the beneficiaries of intense activities of research are not only the territorial areas where these initiatives are carried out, but more in general all the areas connected through business linkages and trade relationships (Autant-Bernard and LeSage, 2011; Tientao et al., 2016). Policy makers tend to exploit R&D investments mainly as an instrument to promote mechanisms of long term economic growth (Prettner and Werner, 2016). With such large total effects for this sector, we provide evidence of immediate significant externalities corroborating the strong relationship between R&D expenditures and economic growth.

Coherently with our estimates in section 5.1, we confirm that *Transportation* expenditures generate benefits for the EU regions directly receiving these funds. Moreover, the positive significant indirect effects suggest that the benefits are spread across locations, and that the core area is not achieving higher gains at the expense of the periphery (Puga, 2008). In addition, this type of expenditure produces the highest total effect among the recipient sectors. Since *Transportation* is the sector receiving the highest portion of the EU budget, this result is of utmost relevance for the design of these finacial aid programmes.

We also find positive direct and indirect effects for SCFs in the *Rural Development* sector, while negative spillovers in the *Environment* sector. On the other hand, we do not find significant spillovers for the *IT Infrastructures*, *Social Infrastructures* and *Tourism* sectors.

We then investigate from a geographical perspective the regions generating the highest spillovers. This analysis could support policy makers in the identification of the most reactive areas contributing to generate cross fertilisation of other member states economies. To

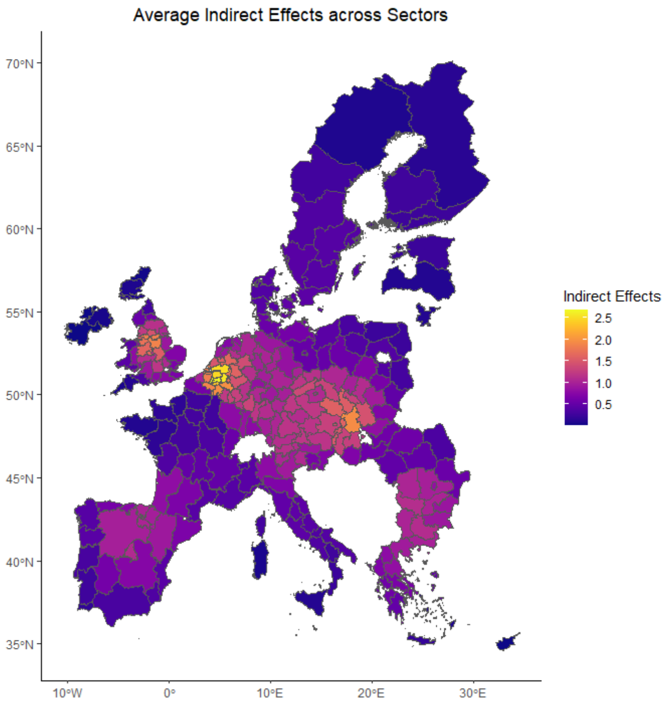

Figure 1: Geographical distribution of indirect effects. For each NUTS 2 indirect effects are computed as the average of indirect effects generated across different sectors.

do so, we compute for each NUTS 2 the average indirect effects generated across all different sectors (see Figure 1). In particular, we find that single regions producing the largest externalities are concentrated in Belgium (see Table 8). For instance, this area has been financed by the "INTERREG Grensregio Vlaanderen-Nederland 2007-2013" programme, a cross regional project involving 28 NUTS 3 of Belgium and the Netherlands with a total budget around 190 million euros. Indeed, this programme aimed to stimulate cross regional development through investments in research and innovation activities, ecological risk prevention, knowledge transfers and business support initiatives.[15] By contrast, regions with the lowest spillovers are located in Cyprus, Ireland, Italy, Malta, Spain, Sweden and UK (see Table 9).

For each country we also compute the aggregate indirect and total effects across sectors generated by all local NUTS 2 regions. The highest values refer to Belgium, Germany, the Netherlands and UK. Figure 2 shows the portion of aggregate indirect effects generated by all NUTS 2 in a country and impacting regions of other countries. We highlight for instance that UK retains the largest portion of indirect effects within country generating only 6.6% and 4.8% of spillovers toward France and Ireland, respectively, while Spain absorbs almost 60% of indirect

[15] Additional information on "INTERREG Grensregio Vlaanderen-Nederland 2007-2013" Programme is available at the following link: `https://ec.europa.eu/regional_policy/en/atlas/programmes/2007-2013/crossborder/operational-programme-belgium-netherlands`.

Table 8: Top 10 NUTS 2 in terms of indirect effects generated.

Country	NUTS 2	Indirect Effects	Total Effects
Belgium	BE24	2.674	2.773
Belgium	BE22	2.574	2.667
Belgium	BE10	2.549	2.646
Netherlands	NL41	2.498	2.591
Belgium	BE21	2.475	2.571
Belgium	BE31	2.356	2.448
Belgium	BE33	1.962	2.043
Belgium	BE35	1.956	2.038
Slovakia	SK02	1.943	2.030
Belgium	BE32	1.886	1.972

Table 9: Bottom 10 NUTS 2 in terms of indirect effects generated.

Country	NUTS 2	Indirect Effects	Total Effects
Ireland	IE02	0.012	0.062
Cyprus	CY00	0.015	0.065
United Kingdom	UKM7	0.032	0.084
Malta	MT00	0.046	0.097
United Kingdom	UKN0	0.049	0.101
Italy	ITI3	0.063	0.114
United Kingdom	UKK3	0.070	0.122
United Kingdom	UKM8	0.078	0.132
Sweden	SE33	0.082	0.138
Spain	ES13	0.083	0.137

effects generated by Portugal. Italy, France, Germany and Sweden receive spillovers from a large number of countries, while Belgium generates significant indirect effects in France, Germany and the Netherlands.

Benefits cross-cutting national boundaries may contribute to a more integrated business environment. To complement findings of Figure 2, we also report the portion of indirect effects that is absorbed by other NUTS 2 regions within the same country. We find that for instance Greece, Italy, Spain and UK retain a largest portion of benefits within the country, with percentages ranging between 52%-87% (see Table 10). Conversely, Austria, Belgium, France, Germany and the Netherlands generate a large amount of spillovers absorbed by NUTS 2 in other countries, with only a percentage between 13% and 38% that is confined within national boundaries.

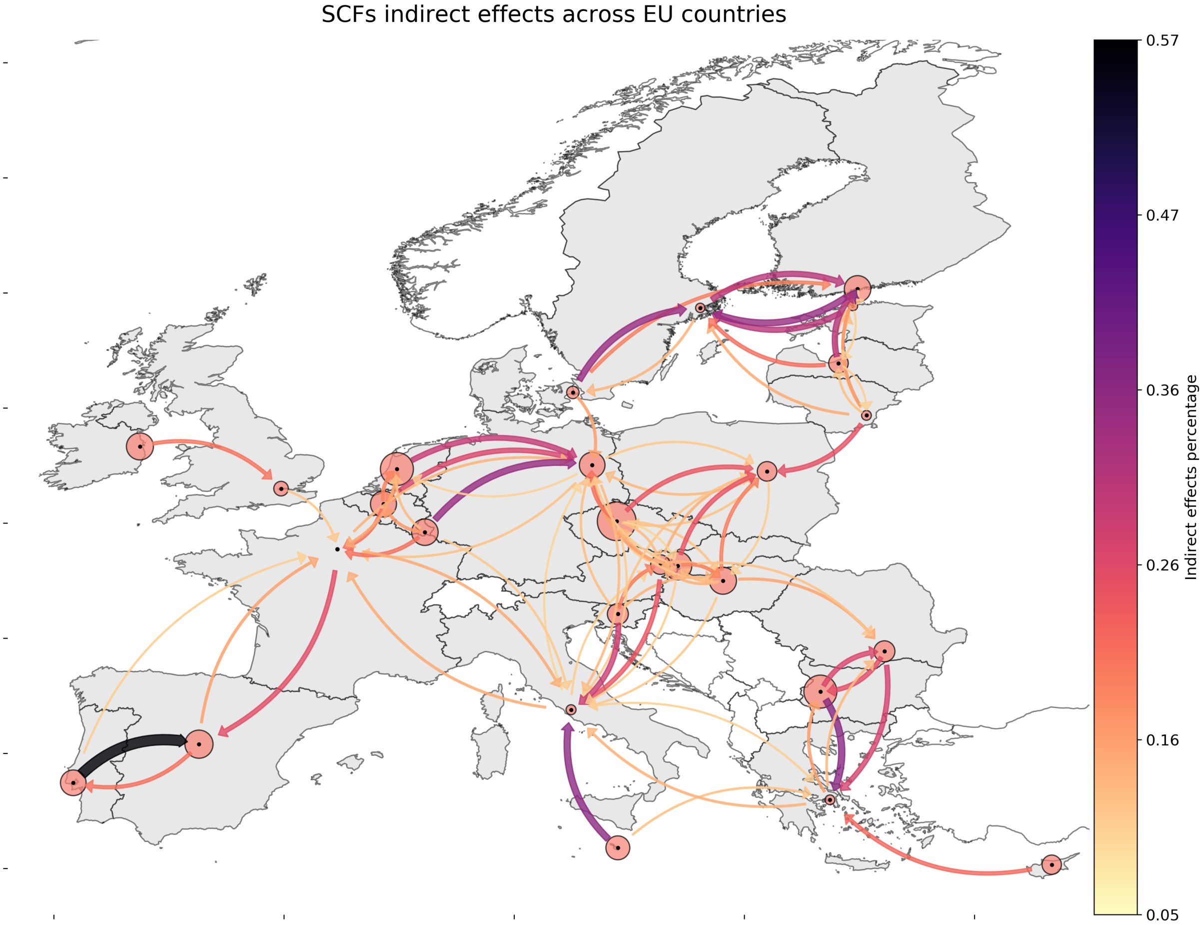

Figure 2: Percentage of indirect effects across different EU countries. We filter indirect effects below 5% with respect to spillovers generated by NUTS 2 in the underlying country.

6 Conclusion

This paper discusses the economic impact of SCFs on European NUTS 2 regions. In particular, differently from previous studies, we investigate whether recipient sectors of EU funds have a key role in terms of GDP per capita growth experienced by NUTS 2 regions. We also aim to assess the immediate impact and medium-long term effects of SCFs and the spillovers generated by investments in different sectors. In this way, we identify the critical sectors which have a more positive impact on regional economic growth. Moreover, it contributes to clarify the effects of different types of investment, especially with respect to those sectors where extant studies provide mixed results.

Cross-section, panel and spatial models indicate that the *Transportation* sector, which is the recipient of the largest amount of SCFs over the period 2007-2014, generates a positive impact in terms of economic growth and medium-long term benefits, suggesting structural improvements of the local infrastructure system. This is in line with past evidence, indicating how EU regions

Table 10: Indirect and total effects generated by EU countries with indication of the amount of spillovers retained within country.

Country	Indirect Effects	Indirect Effects within	Total Effects
Austria	10.741	1.385	11.401
Belgium	22.469	4.379	23.419
Bulgaria	6.018	1.334	6.546
Cyprus	0.015	0.000	0.065
Czech Republic	10.414	1.294	11.007
Denmark	2.118	0.403	2.435
Estonia	0.235	0.006	0.297
Finland	4.981	0.466	5.425
France	8.947	3.370	10.384
Germany	38.601	13.970	41.202
Greece	5.724	4.661	6.540
Hungary	6.393	1.004	6.889
Ireland	0.012	0.000	0.062
Italy	10.994	5.719	12.365
Latvia	0.102	0.000	0.156
Lithuania	0.103	0.000	0.158
Luxembourg	1.303	0.000	1.375
Malta	0.046	0.000	0.097
Netherlands	16.100	3.621	17.022
Poland	9.245	3.459	10.273
Portugal	1.192	0.257	1.453
Romania	5.257	1.467	5.848
Slovakia	5.666	0.376	5.984
Slovenia	1.353	0.039	1.482
Spain	9.688	7.305	10.903
Sweden	2.789	1.074	3.313
United Kingdom	32.151	28.122	34.909

still need improvements in the quality of their transport infrastructures in order to promote economic development. Moreover, it shows that the level of saturation in the infrastructure systems of NUTS 2 regions, which might significantly reduce the returns of new investments in the Transportation sector, has not been reached yet.

Similarly, a positive effect is associated to the *R&D* sector, highlighting immediate benefits of this type of expenditures that persist for up to three years after the investment. Since different authors have documented that policy makers, especially in periods of higher market uncertainty, tend to reduce investments in innovative sectors, privileging more traditional industries, with our study we provide evidence of positive immediate and medium-term impacts for the R&D sector.

Other positive impacts are identified for the *Energy* and the *Human Resources* sectors. The latter is particularly interesting, as with less than 1 € billion it receives only about 0.5% of the overall EU budget. Due to the solid consensus in the literature with respect to the relevant contribution of skilled and educated human capital to economic development, policy makers might consider larger investments in this sector, especially in lagging NUTS 2 regions.

Overall, these results seem to be justified by the neoclassical growth theory, proposing investments in hard infrastructures, human capital (Solow, 1956) and technology (Romer, 1994) as relevant drivers of local development which foster improvements in accessibility, productivity, innovation and reduction of production costs.

Interestingly, we also find that EU regions exhibit stronger economic growth in case they receive less concentrated investments across sectors, showing that *diversification* and complementarity of expenditures can activate more effective patterns of local development. This result provides evidence in favour of comprehensive policy packages, targeting simultaneously different sectors to generate coordinated improvements and achieve consistent level of maturity across industries, thus maximizing potential local growth.

On the other hand, the *Environment* sector, accounting for a significant portion of the overall SCFs (around 16%), displays a slightly negative immediate impact, with negative spillovers. Due to the increasing relevance that this sector will assume in the investment portfolio of the EC in the next programming period, we highlight that this type of expenditure could present a trade-off between economic growth and environmental sustainability. Importantly, positive effects are estimated in the years after the SCFs expenditure.

We also discover that relevant externalities arise according to both spatial and technological weight matrices. In particular, we identify that investments in the *Energy*, *Human Resources*, *R&D* and *Transportation* sectors tend to generate high positive direct and indirect effects. Large spillovers are experienced by NUTS 2 regions in Belgium, the Netherlands and Slovakia, with benefits cross-cutting national boundaries. Overall, a deeper knowledge of how different sectors contribute to economic outcome of both areas directly receiving funds and similar regions in terms of geographical and technological proximity might support policy makers to identify more effective financial aid strategies.

Our analysis presents some limitations. SCFs deployed by sectors for each NUTS 2 are based on our reconstruction of the real data. Although our dataset provides high correlation with respect to the aggregate data disclosed by the EC, this variable might suffer from measurement errors. As a consequence, future contributions might be related to a further refinement in terms of the quality of such information. Also, we analyse the effects generated by SCFs deployed by the main recipient sectors, without focusing on any specific industry. An additional future research direction might be associated to vertical studies on specific sectors in order to investigate their contribution to the local economic development and detect the conditions under which they turn to be more effective.

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A List of the analysed NUTS 2 regions

In this section we disclose the list of NUTS 2 that we employ in our analysis (see Table A1 and A2).

Table A1: List of the analysed NUTS 2 regions. Part I

AT11	Burgenland..AT.	DE25	Mittelfranken	EL54	Ipeiros
AT12	Niederösterreich	DE26	Unterfranken	EL61	Thessalia
AT13	Wien	DE27	Schwaben	EL62	Ionia Nisia
AT21	Kärnten	DE30	Berlin	EL63	Dytiki Ellada
AT22	Steiermark	DE40	Brandenburg	EL64	Sterea Ellada
AT31	Oberösterreich	DE50	Bremen	EL65	Peloponnisos
AT32	Salzburg	DE60	Hamburg	ES11	Galicia
AT33	Tirol	DE71	Darmstadt	ES12	Principado de Asturias
AT34	Vorarlberg	DE72	Gießen	ES13	Cantabria
BE10	Bruxelles-Capitale	DE73	Kassel	ES21	País Vasco
BE21	Antwerpen	DE80	Mecklenburg-Vorpommern	ES22	Comunidad Foral de Navarra
BE22	Limburg (BE)	DE91	Braunschweig	ES23	La Rioja
BE23	Oost-Vlaanderen	DE92	Hannover	ES24	Aragón
BE24	Vlaams-Brabant	DE93	Lüneburg	ES30	Comunidad de Madrid
BE25	West-Vlaanderen	DE94	Weser-Ems	ES41	Castilla y León
BE31	Brabant wallon	DEA1	Düsseldorf	ES42	Castilla-la Mancha
BE32	Hainaut	DEA2	Köln	ES43	Extremadura
BE33	Liège	DEA3	Münster	ES51	Cataluña
BE34	Luxembourg (BE)	DEA4	Detmold	ES52	Comunidad Valenciana
BE35	Namur	DEA5	Arnsberg	ES61	Andalucía
BG31	Severozapaden	DEB1	Koblenz	ES62	Región de Murcia
BG32	Severen tsentralen	DEB2	Trier	FI19	Länsi-Suomi
BG33	Severoiztochen	DEB3	Rheinhessen-Pfalz	FI1B	Helsinki-Uusimaa
BG34	Yugoiztochen	DEC0	Saarland	FI1C	Etelä-Suomi
BG41	Yugozapaden	DED2	Dresden	FI1D	Pohjois- ja Itä-Suomi
BG42	Yuzhen tsentralen	DED4	Chemnitz	FI20	Åland
CY00	Kypros	DED5	Leipzig	FR10	Île de France
CZ01	Praha	DEE0	Sachsen-Anhalt	FR21	Champagne-Ardenne
CZ02	Strední Cechy	DEF0	Schleswig-Holstein	FR22	Picardie
CZ03	Jihozápad	DEG0	Thüringen	FR23	Haute-Normandie
CZ04	Severozápad	DK01	Hovedstaden	FR24	Centre - Val de Loire
CZ05	Severovýchod	DK02	Sjælland	FR25	Basse-Normandie
CZ06	Jihovýchod	DK03	Syddanmark	FR26	Bourgogne
CZ07	Strední Morava	DK04	Midtjylland	FR30	Nord-Pas-de-Calais
CZ08	Moravskoslezsko	DK05	Nordjylland	FR41	Lorraine
DE11	Stuttgart	EE00	Eesti	FR42	Alsace
DE12	Karlsruhe	EL30	Attiki	FR43	Franche-Comté
DE13	Freiburg	EL41	Voreio Aigaio	FR51	Pays-de-la-Loire
DE14	Tübingen	EL42	Notio Aigaio	FR52	Bretagne
DE21	Oberbayern	EL43	Kriti	FR53	Poitou-Charentes
DE22	Niederbayern	EL51	Anatoliki Makedonia	FR61	Aquitaine
DE23	Oberpfalz	EL52	Kentriki Makedonia	FR62	Midi-Pyrénées
DE24	Oberfranken	EL53	Dytiki Makedonia	FR63	Limousin

Table A2: List of the analysed NUTS 2 regions. Part II

FR71	Rhône.Alpes	NL23	Flevoland	SI03	Zahodna.Slovenija
FR72	Auvergne	NL31	Utrecht	SI04	Vzhodna Slovenija
FR81	Languedoc-Roussillon	NL32	Noord-Holland	SK01	Bratislavský kraj
FR82	Provence-Alpes-Côte d'Azur	NL33	Zuid-Holland	SK02	Západné Slovensko
FR83	Corse	NL34	Zeeland	SK03	Stredné Slovensko
HU10	Közép-Magyarország	NL41	Noord-Brabant	SK04	Východné Slovensko
HU21	Közép-Dunántúl	NL42	Limburg (NL)	UKC1	Tees Valley and Durham
HU22	Nyugat-Dunántúl	PL11	Lódzkie	UKC2	Northumberland
HU23	Dél-Dunántúl	PL12	Mazowiecki regionalny	UKD1	Cumbria
HU31	Észak-Magyarország	PL21	Malopolskie	UKD3	Greater Manchester
HU32	Észak-Alföld	PL22	Slaskie	UKD4	Lancashire
HU33	Dél-Alföld	PL31	Lubelskie	UKD6	Cheshire
IE02	South East (UK)	PL32	Podkarpackie	UKD7	Merseyside
ITC1	Piemonte	PL33	Swietokrzyskie	UKE1	East Yorkshire
ITC2	Valle d'Aosta	PL34	Podlaskie	UKE2	North Yorkshire
ITC3	Liguria	PL41	Wielkopolskie	UKE3	South Yorkshire
ITC4	Lombardia	PL42	Zachodniopomorskie	UKE4	West Yorkshire
ITF1	Abruzzo	PL43	Lubuskie	UKF1	Derbyshire
ITF2	Molise	PL51	Dolnoslaskie	UKF2	Leicestershire, Rutland
ITF3	Campania	PL52	Opolskie	UKF3	Lincolnshire
ITF4	Puglia	PL61	Kujawsko-Pomorskie	UKG1	Herefordshire
ITF5	Basilicata	PL62	Warminsko-Mazurskie	UKG2	Shropshire
ITF6	Calabria	PL63	Pomorskie	UKG3	West Midlands
ITG1	Sicilia	PT11	Norte	UKH1	East Anglia
ITG2	Sardegna	PT15	Algarve	UKH2	Bedfordshire
ITH1	Prov. Autonoma di Bolzano	PT16	Centro (PT)	UKH3	Essex
ITH2	Prov. Autonoma di Trento	PT18	Alentejo	UKI1	Outer London - West
ITH3	Veneto	RO11	Nord-Vest	UKI2	Inner London - East
ITH4	Friuli-Venezia Giulia	RO12	Centru	UKI3	Inner London - West
ITH5	Emilia-Romagna	RO21	Nord-Est	UKJ1	Berkshire
ITI1	Toscana	RO22	Sud-Est	UKJ2	Surrey, Sussex
ITI2	Umbria	RO31	Sud - Muntenia	UKJ3	Hampshire
ITI3	Marche	RO32	Bucuresti - Ilfov	UKJ4	Kent
ITI4	Lazio	RO41	Sud-Vest Oltenia	UKK1	Gloucestershire
LT00	Lietuva	RO42	Vest	UKK2	Dorset and Somerset
LU00	Luxembourg	SE11	Stockholm	UKK3	Cornwall
LV00	Latvija	SE12	Östra Mellansverige	UKK4	Devon
MT00	Malta	SE21	Småland med öarna	UKL1	West Wales
NL11	Groningen	SE22	Sydsverige	UKL2	East Wales
NL12	Friesland (NL)	SE23	Västsverige	UKM2	Eastern Scotland
NL13	Drenthe	SE31	Norra Mellansverige	UKM3	South West (UK)
NL21	Overijssel	SE32	Mellersta Norrland	UKM5	North Eastern Scotland
NL22	Gelderland	SE33	Övre Norrland	UKN0	Northern Ireland (UK)

B Data Validation

In this section we assess the robustness of the data we use in the empirical analysis. In particular, we evaluate whether the procedure we employ to build the dataset of annual EU transfers deployed by sector produces consistent results with respect to the official values provided by the EC.

First we check the interplay between the cumulated SCFs across all sectors at country level for the period 2007-2014 disclosed by the EC in the "Integrated database of allocations and expenditures" described in section 3.1 and the corresponding value obtained for the panel dataset, through the application of the procedure described in section 3.2. We observe that the data are significantly correlated (correlation between 0.773 and 0.952, p-value ≈ 0 for all sectors, see column 1 of Table B1). Moreover, we perform a set of t-test: for all sectors the p-values are higher than 0.05 with no exceptions (see column 2 of Table B1).

Then, we repeat the previous analysis with higher granularity, to understand if the results are affected by the data aggregation level, or if instead they are robust at different geographical scales. In particular, we compare the cumulated transfers allocated to NUTS 2 for the period 2007-2014 disclosed by the EC database with the corresponding value obtained from the dataset we use in our panel analysis. Also in this case we find positive and statistically significant correlations (correlation between 0.750 and 0.857, p-val ≈ 0, see column 3 of Table B1). Moreover, we are able to accept that the two samples have the same mean for all sectors except Rural Development and Social Infrastructures (see column 4 of Table B1).

Overall, we find higher accuracy in the reconstruction of the dataset at country level and this is coherent with the fact that 45% of the projects we use to build our dataset has information about the allocation of funds by country and not for single NUTS 2. This forced us to allocate the transfers in amounts proportional to the surface area of each region, contributing to introduce some sources of imprecision in our allocation procedure. However, we still find high correlation values and for the majority of sectors we cannot reject the hypothesis that data have the same mean also at NUTS 2 level, which is the granularity we employ in our empirical analysis.

Finally, we analyze whether the share of EU funds we allocate to single sectors is consistent with those that we find in the dataset disclosed by the EC. We find similar results as differences for the majority of sectors are below 2.5% (see Table B2). We obtain the largest distances for the Environment sector, where we overestimate the amount of SCFs expenditures (16.44% vs

20.58%). On the other hand, we slightly underestimate the amount of financial support devoted to the R&D and the Transportation sectors (16.81% with respect to 13.06% and 38.65% with respect to 35.28%). However, we obtain a correlation between the samples equal to 0.971 (p-val $\approx$ 0). The percentages we obtain are also coherent with those disclosed by documents published by the EC for the ex-post evaluation of the programming period 2007-2013[16]. Indeed, they sustain that Transportation is the most financially supported sector, covering more than one third of the overall budget, the Environment sector absorbs around 17% of the overall transfers and the Human Resources sector receives less than 0.5% of the funds. Table B3 shows the descriptive statistics of the SCFs expenditures per capita deployed by sector.

Table B1: Correlations and t-tests between annual aggregated expenditure at country and NUTS 2 level disclosed by the EC and the sum of yearly financial support across all sectors for EU Regions. Columns 1-2 refer to the country level, while columns 3-4 refer to the NUTS 2 level. P-values are reported in parentheses.

	Correlation	t-test	Correlation	t-test
Energy	0.952***	0.013	0.773***	0.026
	(0.000)	(0.990)	(0.000)	(0.979)
Environment	0.773***	-0.765	0.750***	-1.584
	(0.000)	(0.448)	(0.000)	(0.114)
Human Resources	0.837***	-0.460	0.790***	-0.714
	(0.004)	(0.648)	(0.000)	(0.475)
IT Infrastructures	0.830***	-0.891	0.802***	-1.584
	(0.000)	(0.377)	(0.000)	(0.175)
R&D	0.812***	0.792	0.767***	1.562
	(0.000)	(0.432)	(0.000)	(0.183)
Rural Development	0.804***	-1.629	0.789***	-1.803*
	(0.000)	(0.110)	(0.000)	(0.064)
Social Infrastructures	0.819***	1.186	0.783***	1.791*
	(0.000)	(0.243)	(0.000)	(0.087)
Tourism	0.891***	-1.345	0.784***	-0.910
	(0.000)	(0.185)	(0.000)	(0.303)
Transportation	0.930***	0.232	0.857***	0.578
	(0.000)	(0.818)	(0.000)	(0.563)
Note:		*p<0.1; **p<0.05; ***p<0.01		

[16]See the EC document available at the following link: `https://ec.europa.eu/regional_policy/en/information/publications/evaluations/2016/commission-staff-working-document-ex-post-evaluation-of-the-erdf-and-cohesion-fund-2007-13`.

Table B2: Expenditure percentage of EU funds by sector.

	EC Dataset	Author's estimates
Energy	6.69%	6.66%
Environment	16.44%	20.58%
Human Resources	0.45%	0.52%
IT Infrastructures	4.38%	5.84%
R&D	16.81%	13.06%
Rural Development	3.94%	6.25%
Social Infrastructures	8.42%	5.44%
Tourism	4.22%	6.37%
Transportation	38.65%	35.28%

Table B3: Descriptive statistics of SCFs expenditures per capita at NUTS 2 level deployed by sector.

	Q1	Median	Q3	Std.Dev
SCF: Energy	0.050	0.586	4.117	24.823
SCF: Environment	0.385	3.285	22.042	46.360
SCF: Human Resources	0.000	0.024	0.288	2.350
SCF: IT Infrastructures	0.190	1.327	5.664	14.934
SCF: R&D	0.487	2.473	10.334	35.537
SCF: Rural Development	0.017	1.501	5.959	21.717
SCF: Social Infrastructures	0.000	0.048	3.695	19.652
SCF: Tourism	0.049	1.273	6.998	13.923
SCF: Transportation	0.001	2.070	37.306	71.514
SCF Concentration	0.246	0.318	0.435	0.163

C Check Comparability NUTS 2

In this section we show the results of t-tests performed on a set of socio-economic observable characteristics of European NUTS 2 after the restriction of the analysed dataset through the common support condition described in Equation 7. These t-tests are performed for each sector in which SCFs are spent. In particular, these tests compare observations in one group with respect to all observations in other groups. We show that in the majority of cases we are to accept that groups display comparable socio-economic characteristics (see Tables C1, C2, C3, C4, C5, C6, C7).

Table C1: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the Energy sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.006	0.047	0.521	0.000
Capital Formation	0.916	0.811	0.089	0.009
Population Growth	0.004	0.878	0.102	0.158
Schooling	0.537	0.994	0.517	0.264
Empl A	0.020	0.602	0.441	0.074
Empl B-E	0.088	0.524	0.899	0.037
Empl F	0.108	0.128	0.541	0.031
Empl G-J	0.898	0.370	0.463	0.873
Empl K-N	0.404	0.224	0.698	0.143

Table C2: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the Environment sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.001	0.121	0.052	0.000
Capital Formation	0.012	0.084	0.403	0.653
Population Growth	0.188	0.080	0.327	0.047
Schooling	0.006	0.995	0.121	0.638
Empl A	0.000	0.057	0.631	0.000
Empl B-E	0.218	0.954	0.685	0.576
Empl F	0.228	0.266	0.401	0.105
Empl G-J	0.037	0.712	0.007	0.449
Empl K-N	0.011	0.284	0.032	0.000

Table C3: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the IT Infrastructures sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.000	0.437	0.275	0.000
Capital Formation	0.247	0.081	0.241	0.014
Population Growth	0.005	0.121	0.668	0.006
Schooling	0.244	0.079	0.190	0.795
Empl A	0.000	0.867	0.402	0.027
Empl B-E	0.005	0.124	0.807	0.288
Empl F	0.006	0.253	0.117	0.026
Empl G-J	0.309	0.743	0.630	0.006
Empl K-N	0.000	0.720	0.175	0.000

Table C4: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the R&D sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.006	0.042	0.393	0.000
Capital Formation	0.110	0.716	0.978	0.083
Population Growth	0.180	0.857	0.486	0.020
Schooling	0.176	0.770	0.092	0.525
Empl A	0.190	0.016	0.664	0.007
Empl B-E	0.492	0.594	0.151	0.465
Empl F	0.060	0.100	0.178	0.043
Empl G-J	0.015	0.073	0.315	0.019
Empl K-N	0.004	0.533	0.253	0.000

Table C5: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the Rural Development sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.240	0.203	0.903	0.001
Capital Formation	0.121	0.102	0.823	0.615
Population Growth	0.740	0.028	0.318	0.370
Schooling	0.026	0.331	0.407	0.954
Empl A	0.704	0.568	0.081	0.215
Empl B-E	0.529	0.739	0.678	0.974
Empl F	0.237	0.379	0.082	0.302
Empl G-J	0.199	0.200	0.095	0.013
Empl K-N	0.380	0.264	0.560	0.201

Table C6: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the Tourism sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.013	0.273	0.730	0.000
Capital Formation	0.410	0.805	0.207	0.015
Population Growth	0.002	0.389	0.272	0.000
Schooling	0.981	0.498	0.631	0.816
Empl A	0.041	0.455	0.005	0.010
Empl B-E	0.008	0.629	0.352	0.052
Empl F	0.130	0.096	0.594	0.650
Empl G-J	0.084	0.711	0.797	0.000
Empl K-N	0.207	0.668	0.076	0.000

Table C7: P-values of t-tests on a set of socio-economic characteristics of EU NUTS 2. The dataset is restricted according to the common support condition described in Equation 7 with reference to SCFs expenditures in the Transportation sector.

	Group 1	Group 2	Group 3	Group 4
Initial GDPpc	0.003	0.016	0.391	0.000
Capital Formation	0.076	0.788	0.878	0.137
Population Growth	0.152	0.006	0.216	0.000
Schooling	0.560	0.327	0.594	0.386
Empl A	0.019	0.001	0.276	0.001
Empl B-E	0.733	0.076	0.675	0.040
Empl F	0.620	0.258	0.565	0.606
Empl G-J	0.007	0.927	0.000	0.242
Empl K-N	0.019	0.065	0.009	0.000

D Spatial Durbin Model and Technological Spillovers

In this section we present the estimate of the SDM used to compute the direct and indirect effects in section 5.4. We omit the coefficient of the economic structure since the interest here is only on the coefficients of expenditures by sector and their spatial lags (see Table D1).

Tables D2, D3 and D4 show direct and indirect effects computed with technological proximity matrices based on the estimation of models of Table D1.

Table D1: Estimation of a SDM as in (3) under different specifications of the weight matrix. Standard errors are reported in parentheses.

	Dependent variable: GDP per capita growth			
	Spatial	GDP	Patents	GDP by sector
lambda	0.918***	0.960***	1.168***	1.249***
	(0.012)	(0.015)	(0.098)	(0.047)
Energy	0.093***	0.084***	0.078***	0.076***
	(0.017)	(0.018)	(0.018)	(0.018)
Environment	0.011	0.014	-0.008	0.004
	(0.021)	(0.021)	(0.020)	(0.020)
Human Resources	0.047**	0.043**	0.067***	0.054***
	(0.018)	(0.018)	(0.019)	(0.018)
IT Infrastructures	0.027	0.030	-0.001	0.009
	(0.020)	(0.020)	(0.019)	(0.019)
R&D	0.088***	0.084***	0.069***	0.074***
	(0.017)	(0.017)	(0.017)	(0.017)
Rural Development	0.041***	0.031*	0.032**	0.029*
	(0.016)	(0.016)	(0.016)	(0.016)
Social Infrastructures	0.023	0.015	0.012	0.006
	(0.021)	(0.021)	(0.022)	(0.021)
Tourism	-0.002	-0.008	-0.012	-0.010
	(0.019)	(0.019)	(0.019)	(0.019)
Transportation	0.135***	0.121***	0.079***	0.098***
	(0.022)	(0.023)	(0.022)	(0.022)
Lag Energy	0.061*	0.370***	0.103	0.138
	(0.037)	(0.132)	(0.097)	(0.102)
Lag Environment	-0.116**	-0.307**	-0.048	-0.293**
	(0.050)	(0.135)	(0.062)	(0.146)
Lag Human Resources	0.028	0.305***	0.136	0.030
	(0.030)	(0.104)	(0.098)	(0.115)
Lag IT Infrastructures	-0.001	-0.232*	-0.034	-0.121
	(0.057)	(0.132)	(0.116)	(0.119)
Lag R&D	0.050**	0.209*	0.060	0.125
	(0.023)	(0.118)	(0.086)	(0.096)
Lag Rural Development	0.046*	-0.485***	-0.062	-0.166*
	(0.027)	(0.188)	(0.083)	(0.096)
Lag Social Infrastructures	-0.033	-0.349**	-0.134*	0.035
	(0.042)	(0.160)	(0.077)	(0.134)
Lag Tourism	-0.043	0.087	-0.128*	-0.162
	(0.050)	(0.256)	(0.066)	(0.150)
Lag Transportation	0.125**	0.222**	0.057	0.055
	(0.062)	(0.092)	(0.104)	(0.132)
Observations	2064	2064	2064	2064
Control Variables	Yes	Yes	Yes	Yes
AIC	3532.45	3736.51	3742.59	3736.45
BIC	3713.97	3918.03	3924.11	3917.97
Note:				*p<0.1; **p<0.05; ***p<0.01

Table D2: Spatial Spillovers for EU funds under the technological similarity weight matrix based on GDP per capita. Standard errors are reported in parentheses.

	Direct Effects	Indirect Effects	Total Effects
Energy	0.091***	1.495***	1.587***
	(0.015)	(0.356)	(0.361)
Environment	0.010	-0.967***	-0.957***
	(0.016)	(0.364)	(0.368)
Human Resources	0.048***	1.150***	1.199***
	(0.015)	(0.280)	(0.284)
IT Infrastructures	0.026	-0.655*	-0.630*
	(0.016)	(0.339)	(0.342)
R&D	0.088***	0.935*	1.023*
	(0.014)	(0.563)	(0.567)
Rural Development	0.024*	-1.528***	-1.504***
	(0.013)	(0.495)	(0.497)
Social Infrastructures	0.009	-1.116***	-1.107***
	(0.017)	(0.356)	(0.360)
Tourism	-0.006	0.275	0.268
	(0.015)	(0.624)	(0.627)
Transportation	0.126***	1.109***	1.235***
	(0.019)	(0.254)	(0.259)

Note: *p<0.1; **p<0.05; ***p<0.01

Table D3: Spatial Spillovers for EU funds under the technological weight matrix based on sectoral patents. Standard errors are reported in parentheses.

	Direct Effects	Indirect Effects	Total Effects
Energy	0.083***	1.337	1.420
	(0.018)	(1.106)	(1.113)
Environment	-0.009	-0.384	-0.392
	(0.017)	(0.530)	(0.537)
Human Resources	0.073***	1.482	1.555
	(0.018)	(1.163)	(1.172)
IT Infrastructures	-0.003	-0.198	-0.202
	(0.017)	(0.762)	(0.768)
R&D	0.073***	0.911	0.984
	(0.015)	(0.759)	(0.763)
Rural Development	0.033***	-0.196	-0.163
	(0.013)	(0.539)	(0.540)
Social Infrastructures	0.008	-0.800	-0.792
	(0.019)	(0.682)	(0.687)
Tourism	-0.016	-0.963	-0.979
	(0.017)	(0.746)	(0.751)
Transportation	0.083***	0.969	1.052
	(0.020)	(0.930)	(0.936)

Note: *p<0.1; **p<0.05; ***p<0.01

Table D4: Spatial Spillovers for EU funds under the technological similarity specification for the weight matrix based on sectoral GDP. Standard errors are reported in parentheses.

	Direct Effects	Indirect Effects	Total Effects
Energy	0.087***	2.287*	2.374*
	(0.017)	(1.264)	(1.272)
Environment	-0.008	-2.804*	-2.811*
	(0.018)	(1.672)	(1.679)
Human Resources	0.058	0.945	1.003
	(0.017)	(0.987)	(0.994)
IT Infrastructures	0.004	-1.020	-1.016
	(0.017)	(1.020)	(1.027)
R&D	0.083***	2.088*	2.170*
	(0.015)	(1.105)	(1.110)
Rural Development	0.025*	-1.271	-1.246
	(0.014)	(0.916)	(0.922)
Social Infrastructures	0.007	0.416	0.423
	(0.018)	(1.045)	(1.052)
Tourism	-0.017	-1.709	-1.725
	(0.016)	(1.353)	(1.359)
Transportation	0.105***	1.710	1.815
	(0.020)	(1.279)	(1.287)
Note:			*p<0.1; **p<0.05; ***p<0.01