CITIES AND REGIONS IN TRANSITION

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Cities and Regions in Transition: Introductory Remarks

Roberta Capello, Andrea Conte°*

1. Global Challenges in Present Times

Economic development is never a smooth ride. It always undergoes through moments of deep transformations, primarily driven by technological advancements that demand a complete overhaul of the economic system. What is, however, unique about today's scenario is the sheer number of disruptive challenges that the economies are facing all at once. On their own and in synergies, the 4.0 technological revolution, the reorganisation of economic global integration modes, the present geopolitical situation, climate change and the COVID-19 pandemic are putting economies through unprecedented levels of restructuring and change, unlike anything seen in modern history.

For at least a decade, the 4.0 technological revolution has been rapidly advancing. The application of new cutting-edge technologies in a wide-ranging technological fields – such as artificial intelligence (AI), robotics, internet of things (IoT), autonomous vehicles, 3D printing, sensors, nano-technologies, biotechnology, energy storage, just to name a few of them (Brynjolfsson, McAfee, 2014; Schwab, 2017) – is so powerful as to potentially bring a massive change in the way people work and communicate, express, inform and entertain themselves, and, finally, do business (Capello, Lenzi, 2021).

The technological advancements driving these changes bring with them a sense of disruption, as the outcome is uncertain and hard to predict. On one hand, disruptive visions of a civilization brought close to a 'near workless-world' is coupled with enthusiastic visions of worldwide interconnected, smart and automated societies and highly efficient production systems, in a way which is unprecedented in human history (Brynjolfsson, McAfee, 2014; Schawb, 2017; Rifkin, 1995). New

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business models emerge from the automation and digitalisation of production manufacturing processes leading to the creation of new digital markets and the rise of Industry 4.0 model. As a result, these radical changes have the potential to skyrocket GDP and productivity growth while substantially alter modern labour markets and leaving inevitably behind those firms (and economic sectors) which do not adapt to the new technological challenges. Indeed, the effects on the labour markets are expected to be rather heavy, with routine and non-routine, manual but also cognitive jobs at risk of displacement (e.g. Acemoglu, Restrepo, 2020; Dixon *et al*., 2019; Dauth *et al*., 2019; Aghion *et al*., 2017; Autor *et al*., 2020; Szalavetz, 2019). In this field a harsh debate is taking place between the views of technological enthusiasts (i.e. Brynjolfsson, McAfee, 2014; World Bank, 2019) and those of technological pessimists (Frey, Osborne, 2017).

The advent of new digital markets is a catalyst for massive transformations, with the potential of tearing down old market structures and creating new ones. It intensifies the isolation, separation, competition between traditional business and large intermediaries who tend to govern market transactions. As a result, a polarisation of ownership takes place, with large intermediaries increasingly exerting control over service markets, large manufacturing firms dominating several customer-oriented product markets and micro-multinationals controlling single worldwide markets. This shift has given rise to new forms of inequality, tensions and contradictions within society and the labour market. Traditional business-as-usual activities compete with large intermediaries. The gig economy flourishes driven by winners-take-all activities. Entrepreneurial activities are operated under strict contracts for employees with large platform owners and gig jobs with no social security contracts have proliferated alongside positions that offer superstar compensations. All these contradictions are sources of social discrimination and inequality (Capello, Lenzi, 2021).

In parallel to the technological transition, there is a notable shift taking place in the modes of economic global integration, with globalisation forces receding after a strong wave of global integration from the mid-1980s to the end of the first decade of the 21st century. The reasons behind this shift are multiple, including changes in geopolitics, growing concerns over the impact of globalisation on inequality, environmental degradation and the challenges posed by the fragmentation of international production. The COVID-19 pandemic has only served to further highlight these shifts and the full extent of its longer-term effects are still far from being clear. The expansion of global value chains, which boomed at the beginning of the 2000, reached its peak in 2007 and has not fully recovered since (WTO, 2019; World Bank, 2019), has also generated a debate on whether this trend will lead to 'deglobalisation' (Shih, 2020; Curran, Eckhardt, 2021). The most likely explanation for the reverse trend of globalisation is that the combination of forces that underpinned the expansion of

GVCs before 2008 eased, while long standing challenges were reinforced and new difficulties emerged. In particular, technological transformations – such as the ones discussed above – may have impacted international trade and production practices by enabling automation so to make developed countries more competitive compared to developing ones (Ganzarain, Errasti, 2016; Jankowska *et al*., 2021).

On the geopolitical front, while China and former Comecon countries in Europe have become deeply integrated into the world economy, the shifting political attitudes of the public opinion in several economic countries towards trade integration might also have served as another factor in the restructuring of GVCs. The already distressed international trading system faced further disruptions under the Trump Administration's actions, such as the undermining of the World Trade Organisation and the imposition of punitive tariffs against China and other trading partners, including the European Union. Retaliatory measures by the Chinese side led to a serious trade dispute between the US and China, with tangible consequences for GVCs (e.g. Cappariello *et al*., 2020). This conflictual US-China relationship seems to persist under the Biden administration, recently exhacerbated by the Russia-Ukraine conflict. The underlying issues of intensified international competition underpinning geopolitics have resulted in changing attitudes on technology transfer, intellectual property rights and a stronger focus on long-term strategic industrial policies by individual states, companies and geopolitical players such as the EU. These developments coexist with the growing global recognition of the existential threat posed by climate change and environmental degradation and the pressing need to develop policies that ensure that production and consumption adapt to this wider imperative. In the EU, this manifests itself in the European Green Deal (European Commission, 2019) and the focus of the EU budget on supporting the objectives of the twin (i.e. digital and green) transition (European Commission, 2022).

The outbreak of the COVID-19 pandemic unleashed a new wave of threats and uncertainty upon an already complicated situation, thus highlighting the fragility and vulnerability of the international organisation of production. As various key production centres entered lockdown, supply chain disruptions highlighted GVC vulnerabilities, particularly in the supply of health-related goods such as personal protective equipment (e.g. face masks) and life-saving mechanical ventilators (Gereffi, 2020; Shawn *et al*., 2021). This crisis – with the real and / or perceived shortage of many intermediate and final products – had major impacts on national and regional economies leading to calls for the reshoring of international production structures in order to make GVCs more resilient (Jankowska *et al*., 2021). However, many have urged caution, arguing that access to global production was a key factor in enabling governments to cope with the rapidly changing demands linked to the pandemic. However, despite these arguments, the perception remains that GVCs expose economies to excessive risks during times of crisis and that higher economic resilience requires shorter value chains, through re-shoring or near-shoring (see also De Backer *et al*., 2016).

The geopolitical situation generated by the Russian invasion of Ukraine exacerbates all challenges Europe faces, causing a rise in uncertainty within Europe and the rest of the world due to the differing potential economic scenarios resulting from this conflict. In light of this, a stronger innovation and industrial policy, previously advocated by the EU institutions as a means to close the productivity gap with other leading countries (e.g., EC, 2010; 2012; 2014; 2019), has been reinvigorated as a solution to address the fragility and vulnerability of the international organisation of production from the COVID pandemic onward.

The implications of climate change are far-reaching, posing a significant threat to human health and calling for a comprehensive overhaul of the economy. Since the Industrial Revolution, average global temperatures have risen, with the majority of this increase occurring after 1980, due to the proliferation of greenhouse gases produced by human activities (Ackva, Halstead, 2021). This pressing issue has prompted major economies to discuss more restrictive environmental policy – with a leading role of the European Union to moderate the negative effects of climate change. All novel normative actions are promoting the principles of the circular economy, i.e. an economy that intends to limit waste and where any waste becomes a resource (Wysokińska, 2016). The traditional linear 'make-use-dispose' economic model has to be replaced with a more sustainable, circular approach which reduces the consumption of new raw materials and the waste and emissions from discharging used material. However, the transition to a circular economy is highly demanding because it calls for a substantial rethinking of the functioning of socio-economic systems, through new approaches to regulation and institutions, cultural and behavioural changes, and organizational, process and product innovation (Prieto-Sandoval *et al*., 2018). All actors within society – i.e., firms, industries, individuals and institutions – should contribute to this transformation by rethinking the design, production, distribution, consumption, and handling of products and materials in all sectors (Jakobsen *et al*., 2021).

While the long-term effects of all the changes above remain uncertain, it is clear that they have already generated different responses at local level, exacerbating inter regional and intergroup inequalities, as suggested in the next section.

2. Local Responses: Cities and Regions in Transition

Technological transformations, global shifts, the new geopolitical framework and the impact of the pandemic bring about transformative processes that will have varying effects on regional and urban systems in terms of growth opportunities.

Regions and cities have different capacities to adapt to these challenges, leading to a mosaic of local success and failures that are difficult to predict.

For instance, regions with strong manufacturing sectors may be able to better reap the advantages of robotisation, while facing at the same time the challenges induced to local jobs by the higher risk of automation. The disruptive effects in local labour markets could be compensated by an increase in the overall efficiency of the local economic system, though it may result in exacerbated regional disparities between adopting and non adopting sectors and regions.

Cities, and especially large cities, will be those where the effects of the digital service economy will be more visibly pronounced (Capello *et al*., 2022). Indeed, it is in cities where the major tension between off-line and online activities, the creation of gig vis-à-vis élite jobs, and the unequal distribution of income in favour of capital over labour take place close to each other. Such tendencies will inevitably increase inequalities between the many fragmented categories of workers and between capital owners with respect to labour ones. Such tendencies will be most pronounced in large cities, loci to both corporate headquarters and low-skilled gig-jobs.

The impact of new globalization trends remains to be seen, as they are expected to affect regional growth differently. The shift towards backshoring and nearshoring of GVCs activities, as advocated by many EU countries, will benefit those regions where the reindustrialisation process will reinforces and revitalize local know-how. However, when reindustrialisation gives rise to new and diversified knowledge, the outcome in terms of productivity gains is unclear. As Capello and Cerisola claim in this book, when reindustrialisation takes place in regions that are specialised in other kinds of sectors than the reindustrialising ones, this will lead to productivity increases when accompanied by high levels of technological transformations. The connection between reindustrialization trends and productivity growth is thus not automatic and varies by regional contexts. Regions must take proactive measures through technological progress and organizational and managerial innovation to achieve local production excellence, regardless of the specific manufacturing sectors involved. This occurrence does not have to be associated with science-based fields and high-tech giants, but can be applicable even to low-tech contexts in which there may be a prevalence of SMEs.

Climate change requires regions to embrace the transition towards a circular economy, i.e. it imposes regions the need to develop the ability to generate new ideas or new combinations that are put into commercial practice in the form of new products, services or processes. This capacity is linked to localized knowledge, accumulated green capabilities, and the interplay with digital complementary technologies present in the regions. As Fusillo and Quatraro show in the book, green and digital complementary localized capabilities in a region enhance its ability to absorb and integrate new technological opportunities in circular economy-based recombinations, representing a crucial leverage for stimulating regional transition.

Last, but not least, the COVID-19 pandemic has affected regions and territories in a different way, not only since the virus has sprawled differently at the spatial level, but also because the mitigating measures put in place differed among countries and regions. From a regional perspective, there is evidence that the pandemic has widened the gap between wealthy and poor areas, between growing and declining places, opening the question on the potential scenarios ahead of us and the effectiveness of the overall policy response – by individual EU countries and at the European level such as in the case of the National Recovery and Resilience Plan (NRRPs) – in relaunching the economy and reabsorbing regional disparities and income inequality. In turn, this highlights the pressing need for further analysis while the issue of better tools for policy monitoring and policy impact assessments is again at the forefront of the scientific agenda.

The reasons behind the different reactions of cities and regions to the above mentioned challenges are yet to be fully understood and require detailed analysis, together with advanced tools for inequality measurement and for territorial policy assessment. This book presents a first attempt in this direction, as presented in the following section.

3. Structure of the Volume

The conference of the Italian Regional Science Association (AISRe), held in September 2022 in Milan, was a great opportunity to start reflecting on the local responses to the important challenges that European territories are facing. Far from being exhaustive on the issue of global challenges and local responses, this book collects a series of contribution that were presented during the conference, in which the main attention is put on local and regional economic systems. It highlights the way cities and regions are grappling with the transformative process that such disruptive challenges impose in terms of shifts in labour markets and working conditions, the increasing urgency of environmental concerns and the push for resource-efficiency and decarbonisation, and the drive to increase productivity and growth through modernisation processes, irrespective of the type of sectoral specialization (high vs. low sectors).

The book is structured in three parts. The first part presents four papers dealing with the recent challenges, and the regional responses to such challenges. Capello and Cerisola enter the debate of reindustrialisation, and claim that the adoption of new 4.0 technologies – like digital automation in manufacturing – in reindustrialization processes is fundamental for productivity gains through reindustrialisation. This is true especially when reindustrialization takes place in areas where a diversified variety of local sectors does not create a critical mass of know-how on which local firms can excel and compete. This applies to both high- and low-tech sectors, supporting the role that can be played by traditional sectors with respect to the usually considered high-tech giants in relaunching productivity. The chapter presents empirical evidence on this claim, thanks to an original database on employment and value added at regional (NUTS2) manufacturing sub-sectors level for the EU members plus the UK. The results show that, while a reindustrialization focused on specialised sectors provides productivity gains irrespective of the level of 4.0 technology adoption in the sectors, a reindustrialization in a variety of local sectors provides productivity increases only if sectors are subject to important technological advances.

The following chapter, authored by Fusillo and Quatraro, presents a reflection on the sustainable transition faced by Europe. It stresses the need for a shift towards a Circular Economy (CE), calling for a deeper understanding of the relationship between innovation, technologies, and CE, which received relatively less attention in existing literature, particularly at the regional scale. This chapter sheds light on this debate by investigating the regional recombinant dynamics of CE technologies and examining the role of localized knowledge, accumulated green capabilities, and the interplay with digital complementary technologies. The empirical analysis is conducted on a dataset of European NUTS2 regions over the period 1985-2015 and suggests that green and digital complementary localized capabilities increase the regional ability to absorb and integrate new technological opportunities in CE-based recombinations, representing a crucial leverage for stimulating regional transition.

Dellisanti describes the role played by creativity as a catalyst for innovation and competitiveness in regions undergoing transition. This chapter aims to discuss the potential of Cultural and Creative Industries (CCIs) to generate virtuous cycles for the recovery of EU regions, taking into account their varying stages of development. This discussion supports the idea that regions in transition can leverage the diverse creative and cultural landscapes to their advantage.

In their work, Neri and Sciclone guide readers towards exploring the evolving nature of poverty and the monitoring of poverty conditions caused by the COVID-19 pandemic. The authors make a concerted effort to estimate non-monetary poverty indicators at two different sub-regional levels in Tuscany using original data obtained from the ad-hoc “Survey on Vulnerability and Poverty” planned and conducted in September 2021 by the Regional Institute for Economic Planning of Tuscany (IRPET) in collaboration with the University of Siena.

The second part of the book is dedicated to novel methods and applications to spatially monitor / analyse socio-economic transformations, focusing in particular on R&I investments, value chains, poverty, wellbeing and firms’ efficiency levels.

The first paper, authored by Conte and Marques Santos, investigates the challenges of mapping EU funding programs and the resulting implications for policy makers. In doing so, this chapter presents a new tool for mapping R&I funding across various EU programmes at territorial level, offering valuable insights for stakeholders interested in designing effective territorial policies for regional and local development.

The second paper, by Ferraresi, Ghezzi and Paniccià, extends the use of interregional input-output tables for assessing the employment embodied in regional value chains – in terms of type of occupations and skills – a crucial tool to measure the effects of GVCs' reorganization. The authors estimate the degree of integration of Italian regions in some important value chains and some value chain – related indices of labor productivity and hourly wages. They develop a new dataset containing information about regional and sector skill content in order to characterize each value chain in terms of demand for skills, knowledge and abilities. Finally, they identify each single regional contribution to the value chains in terms of skills. The results suggest that regions greatly differ in terms of their economic involvement in the value chains, with Northern regions far more involved in value chains characterized by high labor productivity and hourly wages, such as exports and investment goods related value chains. Moreover, the heterogeneity across regions within each value chain is considerably high, with a higher share of highly skilled tasks provided by Northern and Centre regions, even in those value chains where Southern regions appear specialized.

The third paper, by Bernini, Emili and Ferrante, examines how people's subjective well-being adapts to poverty by studying the effect of changes in economic conditions on overall life satisfaction and several domains of life. The analysis investigates whether there are regional disparities in these relationships, looking at the entire country and macro-areas (North vs Center-South) using a statistical matching approach. Results suggest that adaptation is not observed for individuals who enter poverty at the current time or experience a decline in economic conditions. Significant regional differences in the subjective wellbeing – poverty adaptation nexus are found, especially for economic and health domains, highlighting the need for place-based policies to reduce disparities in living conditions.

The fourth paper, by Galli, evaluates the impact of start-ups on a country's economic growth by examining their role in stimulating inventiveness and market dynamics. In this framework, innovation is a key factor for favouring incumbent firms' positive performance, survival and competitiveness. This chapter also examines the role of knowledge spillovers in affecting the efficiency levels of Italian start-ups, and considers the occurrence of productivity and input spillovers across innovative clusters. In doing so, it differentiates between spatial effects arising from intangible investments and firms' patenting activity. The study utilizes georeferenced firm-level data on Italian innovative start-ups between 2018 and 2020, and employs a spatial stochastic frontier model to account for different sources of spatial dependence. The results can aid policy-makers in designing plans and policies to promote start-up competitiveness by leveraging firms' interaction and cooperation.

The third part of the book focuses on the role of cohesion policies in guiding socio-economic transformations.

The first paper, by Coppola, Destefanis, Di Serio and Fragetta, analyses the effectiveness of European policies by measuring the multipliers of EU structural funds (ESIFs) in eighteen Italian administrative regions throughout 1994–2016. They use a Bayesian random effect panel vector autoregressive model to estimate region-specific multipliers and find that ESIFs have large and significant GDP multipliers. They also measure the extent of substitutability between ESIFs and other public expenditure variables, which contradicts the principle of additionality of the EU cohesion policy. A cross-region analysis of multipliers suggests that their values are positively associated with labour slack as well as with technological capability.

The second paper, by Mogila, Brasili and Calia, analyses the impact of Cohesion Policy (CP) on the development of EU NUTS-2 regions in the period 2007-2018, by adopting a beta-convergence model approach and trying to overcome its main limitations, namely endogeneity, spatial relationship and heterogeneity. Results indicate growth convergence between regions and a slightly positive impact of such policies on less developed EU regions, underscoring their role in reducing regional disparities.

The European Cohesion Policy not only has an impact in those regions where it is implemented, but also generates indirect advantages in neighboring or economically connected areas through spillovers. The last two papers focus on this important aspect. The third paper in the third part of this book, by Gambina and Mazzola, assesses the impact of spatial spillovers on the effectiveness of projects financed in Italian provinces (NUTS-3) by cohesion policy during both the 2007-13 and 2014-20 programming periods. The authors use a panel econometric strategy to estimate a spatial panel model which allows to disentangle the effects of the policy on per capita GDP growth both directly (on the treated provinces) and indirectly (spillovers on neighbouring areas). This paper also examines how policy effectiveness and spillover direction changed during the Great Recession and whether regional policy acted as a resilience factor in local economies. The study finds that spatial spillovers play a positive role in enhancing policy effectiveness, but the impact of spillovers reduced significantly during the crisis years, possibly affecting cohesion policy effectiveness. The study is based on registered expenditures related to completed projects from the Opencoesione database.

The last paper, by De Castris, Di Gennaro and Pellegrini, also takes the indirect effects of cohesion policies into account and proposes a way to incorporate spatial spillovers into a classic counterfactual model. In general, this model typically assumes no interference effects between treated and untreated units of the policy (named SUTVA – Stable Unit Treatment Assumption – assumption). This work aims to overcome this restriction, by implementing a methodology fully coherent with the counterfactual approach but relaxing this assumption. The authors propose a spatial difference-in-differences model, based on the Spatial Durbin Model (SDM) specification that allows for spillover effects. The paper evaluates the total effects of regional policy during the 2007-2013 programming period and finds that European regional policy has positive effects, particularly in Eastern regions, by reducing inequalities with more developed regions and producing high positive externalities.

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Part 1

The Recent Challenges

Regional Transformations Processes: Reindustrialization and Technological Upgrading as Drivers of Productivity Gains

Roberta Capello, Silvia Cerisola**

Abstract

Reindustrialization is one of the transformations European economies are expected to go through. It was suggested by the European political institutions as one of the strategies to counteract the productivity stagnation of the last 20-30 years. What is advocated by the European Institutions is a modern reindustrialization, through technological upgrading and transformation. This chapter enters the debate by claiming that the adoption of new 4.0 technologies – like digital automation in manufacturing – in reindustrialization processes is fundamental for productivity gains. This is true especially when reindustrialization takes place in areas where a diversified variety of local sectors does not create a critical mass of know-how on which local firms can excel and compete. This applies to both high- and low-tech sectors, supporting the role that can be played by traditional sectors with respect to the usually considered high-tech giants in relaunching productivity. The chapter presents empirical evidence on this claim, thanks to an original database on employment and value added at regional (NUTS2) manufacturing sub-sectors level for the EU members plus the UK. The results show that, while a reindustrialization focused on specialised sectors provides productivity gains irrespective of the level of 4.0 technology adoption in the sectors, a reindustrialization in a variety of local sectors provides productivity increases only if sectors are subject to important technological advances.

1. Introduction[1]

A long period of productivity stagnation has been characterizing the European performance for the last 20-30 years. This has been highlighted and analyzed from many parts, both at the academic (e.g. Solow, 1987; Brynjolfsson, 1993,

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Acemoglu *et al*., 2014), and at the institutional level (Ortega-Argilés, 2012; van Ark *et al*., 2013; Cette *et al*., 2016; ECB, 2017). Such slowing in productivity dynamics was also associated with the overall shift from manufacturing to services, according to a deindustrialization trend that was clearly observable and that in Western Europe was especially due to the offshoring of activities previously performed in-house (Nickell *et al*., 2008; Tregenna, 2009).

The deindustrialization trend was interpreted as problematic for many reasons. Services depend on a strong manufacturing base for their equipment and material inputs; the main demand for business services comes of course just from the manufacturing sector, which is also the main source of export; lastly, most company R&D takes place in manufacturing. All this implies that the loss of manufacturing compromises long-term productivity growth and living standards (EC, 2015; Ciffolilli, Muscio, 2018).

After the 2008 economic crisis that dramatically affected the global economy, a reindustrialization process was strongly encouraged and explicitly advocated by the EU political institutions (e.g., EC, 2010a, 2012, 2014, 2019) as a possible mean to relaunch productivity. After the COVID period, reindustrialization was further interpreted as an option to recover from the fragility and vulnerability of the international organisation of production. In Tregenna's words (2009, p. 436), "'learning-by-doing' is more important in industry than in agriculture or services; learning-by-doing, innovation and intersectoral linkages thus render overall productivity growth endogenous to growth in dynamic manufacturing sectors. *This of course means that expanding the manufacturing sector would raise manufacturing (and non-manufacturing) productivity*. It is also argued that most technological change occurs in the manufacturing sector".[2]

Despite the wide political interest in reindustrialization as a transformation process, related academic studies are still extremely scant.[3] The present chapter proposes an original contribution especially when it investigates the idea – warmly advocated by the European Institutions – of a modern reindustrialization, implicitly associated to advanced high-tech sectors. The paper overcomes such interpretation by claiming that the linkage between reindustrialization and productivity gains is a matter of the type of local reindustrialization patterns (Capello, Cerisola, 2022) rather than of sectors. Some reindustrialization modes reinforce and renovate local know-how, others instead give rise to new and diversified knowledge. In the former case, we do expect that the reinforcement of local know-how or the creation of a critical mass of local knowledge leads to productivity gains through the accumulation of specific competences. In the latter case, the new diversified knowledge generated by reindustrialisation is

2. Italics added by the authors.
3. Among the few works we are aware of, see Christopherson *et al*., 2014.

expected to generate productivity advantages when this is accompanied by high levels of technological transformations.

This is true irrespective of whether reindustrialization occurs in high- or low-tech sectors. In fact, in the 4.0 technological era, even traditional low-tech sectors can be affected by profound transformations, leading to deep and efficient process innovation through increasing investments in highly skilled labor, advanced machinery that may upgrade production capabilities (Ghosal, Nair-Reichert, 2009; Hansen, Winther, 2011). 4.0 technologies (e.g. digitalization, the Internet of Things, robotics and artificial intelligence) pervade in fact also low-tech sectors, like the textile industry, rapidly penetrating manufacturing operations and management, and leading to the so-called *fourth industrial revolution* or *Industry 4.0* (Brynjolfsson, McAfee, 2014; De Propris, Bailey, 2020; Capello, Lenzi, 2021; 2022).

Exploiting original data on disaggregated manufacturing sub-sectors – collected by contacting each national statistical office in each European country – and on advanced robots, capturing the degree of 4.0 technological adoption, this study investigates the relationship between different forms of regional reindustrialization and productivity growth in different technological transformation contexts.

The chapter is organized as follows. Section 2 explains the conceptual framework, involving the different regional reindustrialization patterns and the related role of industrial technological transformations in the European regions. Section 3 presents the empirical analysis in terms of model and data. Section 4 displays and discusses the econometric results, while Section 5 concludes.

2. Innovation, Reindustrialization and Productivity Gains

Innovations are not necessarily the result of systematic R&D (Boschma, Frenken, 2011; Boschma, 2017, Balland *et al.*, 2019). They can be instead interpreted as the outcome of incremental product development, customer-oriented innovations or the optimization of process technologies (Hirsch-Kreinsen, 2008, p. 27). Shared and localized accumulation of specific knowledge and the socialization of the risk associated with innovative activity are studied as the sources of a competition-driven stimulus to innovate (Camagni, 1991). In a more dynamic perspective, innovation is linked to collective learning processes involving cooperation on industrial projects, tacit transfer of knowledge and public-private partnerships in complex development schemes.[4]

In this vein, a conceptual framework has been recently put forward, based on the strong belief that regions innovate through different modes. Some modes are based on the local creation of new knowledge, others, instead, either creatively adopt new

4. See also Maskell and Malmberg (1999) on the importance of firms' proximity at the local level to create knowledge through interaction and collective learning.

knowledge developed in other regions, or imitate an already existing innovation (Capello, Lenzi, 2018). Interestingly enough, when empirically proved, no mode turned out to be superior to another, and also the mode based on mere imitation was able to generate productivity gains to regions adopting it (Capello, Lenzi, 2013).

Despite this large theoretical debate and the normative reflections that followed and developed in the so called "smart specialisation strategy" of the EU (Foray *et al*. 2012; Foray, 2015; McCann, Ortega-Argilés, 2016), the idea that R&D is *the* fundamental source for a science-based development has in reality never been put aside in the scientific and political literature. As clearly argued by Hansen and Winther (2014), it is often the case that little attention is devoted to the new specificities of low-tech manufacturing and the understanding of innovation in supranational, national, and regional strategies is dominated by a science-based perspective.

The idea that economic growth and employment are mostly the result of research-intensive industries has been indeed labelled 'high-tech myopia' (Heidenreich, 2009), and, in our opinion, we could also refer to 'R&D myopia'. Our overall impression, in fact, is that this attitude towards high-tech and R&D, perceived as the ultimate solutions for growth, has influenced also the debate on reindustrialization. In the official documents of the EU (EC, 2012; EC, 2014; EC, 2019) the reference to a modern reindustrialization for the relaunch of productivity implicitly assumes a science-based reindustrialization process, which could risk neglecting low-tech sectors.

In this perspective, the attention of academia and policy makers therefore should not be exclusively devoted to reindustrialization in high-tech sectors. Even low-tech sectors can achieve productivity gains through innovation, when one overcomes the idea that the capacity to innovate merely depends on R&D and instead embraces the perception that it also depends the rootedness of firms within their own territory. The more rooted they are in terms of productive specialization, the more they can be expected to be competitive, through the fruitful triggering of rejuvenating trends based on knowledge locally cumulated. When these conditions are not present, the adoption of new technologies seems necessary to improve productivity dynamics.

To empirically prove such a statement, this work benefits from a conceptual approach proposed in a previous study (Capello, Cerisola, 2022), in which different patterns of reindustrialization have been proposed, namely:

- ***Reinforcement*** *of the pre-existing specialized industrial fabric,* when reindustrialization occurs in sectors in which the region was already specialized and further increases such specialization;
- ***Shrinkage*** *of the pre-existing industrial fabric towards a new specialization,* when there is a reorientation process towards new sectors that achieve a critical mass, i.e., reindustrialization occurs in sectors in which the region was not initially specialized, but such specialization increases over time;

- ***Diversification*** *of the pre-existing specialized industrial fabric,* when a new diversified path, potentially based on related knowledge, takes place, i.e., reindustrialization occurs in sectors in which the region was already specialized, but such specialization decreases over time, leading to diversification;
- ***Enlargement*** *of the pre-existing diversified industrial fabric,* when a creation of new non-core sectors further widens sectoral diversification without achieving a specialization, i.e., reindustrialization occurs in sectors in which the region was not initially specialized, and such specialization further decreases over time, leading to an enlargement of the existing sectors.

In the *reinforcement* and *shrinkage* types of regional reindustrialization, which are characterized by an increase in the local specialization and therefore by a strong tie with the territory, the probability to enhance productivity exists and is high. Collective learning mechanisms (Aydalot, 1986; Camagni, 1991; Maillat *et al*., 1993) are generated and continuously feed new knowledge, leading to a self-reinforcement process of managerial, organizational, product and process innovation. Instead, in the other two regional reindustrialization patterns, in which reindustrialization leads to an increasing variety of knowledge, the link with productivity gains cannot be given for granted. In this case, local know-how is improved in a fragmented way and collective learning processes do not take place. Inevitably, under these conditions, the effects of a reindustrializing strategy on productivity gains remains doubtful, unless this is not accompanied by a substantial adoption of 4.0 technologies. Through technological progress and organizational and managerial innovation that open to local production excellence, indeed, a relaunch of the local economy can be possible. In fact, a modernization of manufacturing production, in the vein of *Industry 4.0*, can be easily conceptually associated with cost reduction, greater efficiency, higher flexibility, and, consequently, improvements in the dynamic of productivity.

3. Empirical Strategy: Model and Data

In order to explore empirically the linkage between reindustrialization (in its different modes), technological advances, and productivity gains, we estimate the following model (Equation 1) at the regional (NUTS2)[5] level in the EU countries plus UK:

$$\begin{aligned} &\textit{prod growth ind}_{r,\,2013-2018} = \alpha + \beta_1 \textit{reind}_r + \beta_2 \textit{tech}_{r,\,2013} + \beta_3 \textit{hc secondary}_{r,\,2013} + \\ &+\beta_4 \textit{hc tertiary}_{r,\,2013} + \beta_5 R\,\&\,D_{r,\,2013} + \beta_6 \textit{city over mln}_{r,\,2013} + \beta_7 \textit{gdp pc}_{r,\,2013} + \varepsilon \end{aligned} \qquad [1]$$

5. Data for Germany are at NUTS1 level, as well as the city of London (UKI).

where *prod growth ind* is the real industrial labor productivity compound growth rate between 2013 and 2018 in region *r*, and *reind* is a dummy variable equal to one if the region reindustrialized (Table 1).[6] A region is considered as "reindustrializing" when the growth of the share of manufacturing VA over total was greater in a post-crisis period (2013-2017) with respect to a pre-crisis period (2000-2007).[7]

In a subsequent set of estimates, the reindustrialization variable was substituted with dummy variables equal to one if the region reindustrializes according to the specific pattern. These patterns have been identified by applying the reindustrialization definition to nine more disaggregated manufacturing sectors. Considering the initial regional specialization in the reindustrializing sectors (measured through a Location Quotient) and its evolution over the analyzed period (2000-2017), the different patterns of regional reindustrialization were identified (*reinforcement*, *shrinkage*, *diversification*, and *enlargement*). This step has been made possible thanks to a large data gathering effort, since the information on the value added of manufacturing sub-sectors was requested to each single National Statistical Office; when not available, data were carefully estimated.[8] As already highlighted before, the regional reindustrialization patterns are not associated with specific sectors; rather, they are related to particular reindustrialization modes.

The 4.0 technology variable (*tech*) measures the technological progress in reindustrializing sectors. It is built as the share of VA in reindustrializing sectors in which the region has more robots per employee with respect to its country average in those sectors.[9] Considering the country/sectoral average is extremely important here, since there are substantial differences between countries and among sectors within the same country (see also Storper, Walker, 1989; Graetz, Michaels, 2018).

The data source is the International Federation of Robotics. However, the information provided is in terms of count data (number of robots introduced every year) by country and sector. Therefore, the stock of robots was calculated through the Permanent Inventory Method (PIM), with 2006 as the base year[10], considering a 12% depreciation rate, and finally computing an average 2012-2014

6. In general, a region is considered as "reindustrializing" if the share of its manufacturing value added grows more – or loses less – in the post-crisis period (2013-2017) with respect to the pre-crisis one (2000-2007). The reference category is here represented by non-reindustrializing regions.

7. Admittedly, the changes in the share of manufacturing VA are influenced by the changes in the price of services, since the last ones influence the change in the share of service VA at current prices. To control for this possible interference, Table A1 in Annex shows the trend in the relative prices of manufacturing in the two periods of our analysis.

8. Further details are available in Annex and in Capello and Cerisola (2022).

9. On the use of automation to maintain (or bring back) jobs in the home country the reader may refer to Arlbjorn *et al*., 2013 and Arlbjorn, Mikkelsen, 2014.

10. 2006 was chosen as the first year for which the information was available for all countries. This is also consistent with Caselli *et al*. (2021).

Table 1 – Variables' Description

Variable name	*Description*	*Data source*	*Reference period*
prod growth ind	Industrial (B-E) labor productivity (real GDP/employment) compound growth rate (authors' computation)	Cambridge Econometrics*	2013-2018
reind	Dummy var=1 if the region reindustrializes (authors' computation. See text and Annex for details)	Eurostat	2000-2017
reinforcement	Dummy var=1 if the region reindustrializes in manufacturing sectors in which it was initially specialized and such specialization increases over the period (authors' computation)	National Statistical Offices, IGEAT**; Eurostat	2000-2017
shrinkage	Dummy var=1 if the region reindustrializes in manufacturing sectors in which it was not initially specialized, but the specialization increases over the period (authors' computation)	National Statistical Offices, IGEAT**; Eurostat	2000-2017
diversification	Dummy var=1 if the region reindustrializes in manufacturing sectors in which it was initially specialized and such specialization decreases over the period (authors' computation)	National Statistical Offices, IGEAT**; Eurostat	2000-2017
enlargement	Dummy var=1 if the region reindustrializes in manufacturing sectors in which it was not initially specialized, and the specialization further decreases over the period (authors' computation)	National Statistical Offices, IGEAT**; Eurostat	2000-2017
tech	Share of VA in reindustrializing sectors in which the region has more robots per employee with respect to its country average in those sectors (authors' computation)	International Federation of Robotics and Eurostat (for the regionalization of data)	2012-2014
hc secondary	Human capital measured as the share of upper secondary and post-secondary non-tertiary educated over total employment	Eurostat	2013
hc tertiary	Human capital measured as the share of tertiary educated over total employment	Eurostat	2013
R&D	Research and development expenditure over GDP	Eurostat	2013
city over mln	Dummy var=1 if the region hosts a city with more than one million inhabitants	Eurostat	2013
gdp pc	GDP over population	Eurostat	2013

Notes: (*) Cambridge Econometrics was preferred as a data source with respect to Eurostat, since it allowed to cover all the countries (including UK) at NUTS2 level up to 2018. (**) Institute for Environmental Management and Land-use Planning (Institut de Gestion de l'Environnement et d'Aménagement du Territoire – IGEAT), University of Brussels.

value. The period was chosen having in mind ideally 2013 (as the other variables in our econometric model), but being aware that count data, although transformed into stock through PIM, could be volatile.

Technological differences have been shown to be there between sub-national regions and in fact these data are typically regionalized based on the local distribution of the employment in the related sectors. However, we follow Capello and Lenzi (2021; 2022) and embrace a more sophisticated approach, which we believe leads to more precise estimations. Data were in fact regionalized through the use of three weights for which information is available at NUTS2 level: the regional share of population with broadband access (Eurostat), the regional share of blue-collars (plant and machine operators, source Labour Force Survey – LFS), and the regional share of employment by sector (Structural Business Statistics – SBS).

In order to further corroborate our claim that the technological advances measure here developed is not linked to the high-tech sectors, we checked the correlation between our variable and the regional share of employment in high-tech manufacturing sectors over total manufacturing.[11] Such correlation is basically nonexistent (-0.07) and completely statistically insignificant. Similarly, performing an ANOVA on the share of employment in high-tech manufacturing sectors in the different regional reindustrialization patterns, we verified that there is no statistical difference among the patterns, meaning that, even in this case, they are completely unrelated to the presence of high-tech sectors. They are instead representative of particular modes of reindustrialization rather than of advanced sectors, according to a territorial perspective.

Moreover, additional independent variables control for:

- human capital, as a well-known determinant of regional economic growth (Romer, 1986; Lucas, 1988). In this work such asset is considered through two different measures, i.e. the share of upper secondary and post-secondary non-tertiary educated over total employment (*hc secondary*), and the share of tertiary educated over total employment (*hc tertiary*) (see Table 1) to check if what is mostly needed for industrial productivity dynamics is in fact just a higher education level or better technical training[12];
- *R&D*, as an input measure of traditional innovation. This is expected to have a positive coefficient, represented by the share of research and development expenditure over GDP;
- urbanization economies (*city over mln*). These are expected positive and measured through a dummy variable equal to one if the region hosts at least one city with more than one million inhabitants; and

11. Data source: Eurostat.
12. On the potential skill mismatches on the labour market, the reader may also refer to EC (2010b).

- initial level of wealth (*gdp pc*), measured as GDP per capita. This is expected to be negatively related to productivity growth since poorer regions tend to grow faster than richer ones, according to an overall convergence dynamic.

Using the econometric models and the data described in this section, the relationship between reindustrializing regions, in their different regional reindustrialization patterns, and the dynamic of industrial productivity was analyzed, also considering the role of technological transformations, as explained above. The results are presented and discussed in the next section.

4. 4.0 Technologies and Reindustrialization: Empirical Evidence

From the estimate results, displayed in Table 2, interesting messages emerge. First of all, the first two columns show that *reindustrialization matters, especially for high values of technological adoption*.

More specifically, column (1) displays the outcome of the basic equation of the previous section. As can be inferred from the coefficients and their significance, reindustrializing regions perform better than the others, although this does not seem to depend overall on technological adoption. The interaction term between the technology and the reindustrialization variables shows no significance (Column 2, Table 2).

Interestingly enough, however, the marginal effects of reindustrialization (dummy *reind*=1) computed on the specification shown in column (2) are increasing for increasing values of technological adoption. Especially, they become statistically significant for values of technological adoption higher than 40% (Figure 1). Therefore, it appears that 4.0 technologies reinforce productivity gains when they take place in a high share of reindustrializing sectors, suggesting that a critical mass is necessary. Some propagation effects are also visible, since the advantages are registered on the whole industry when reindustrialization is defined on manufacturing only.

Another thought-provoking result is that the type of human capital that is significantly important in this process is the one related to more technical skills, represented by the share of the employees with a secondary level of education. On the other hand, a more classical measure of human capital in terms of tertiary educated employees is not statistically significant when we look at industrial productivity dynamics. As for the other control variables, R&D expenditure is significantly associated with the dependent variable, while – as expected – GDP per capita shows a negative and significant coefficient, representative of poorer regions growing faster than richer ones, according to an overall convergence process.

In order to deepen our understanding on the issue, reindustrializing regions are subsequently disentangled into their specific regional reindustrialization

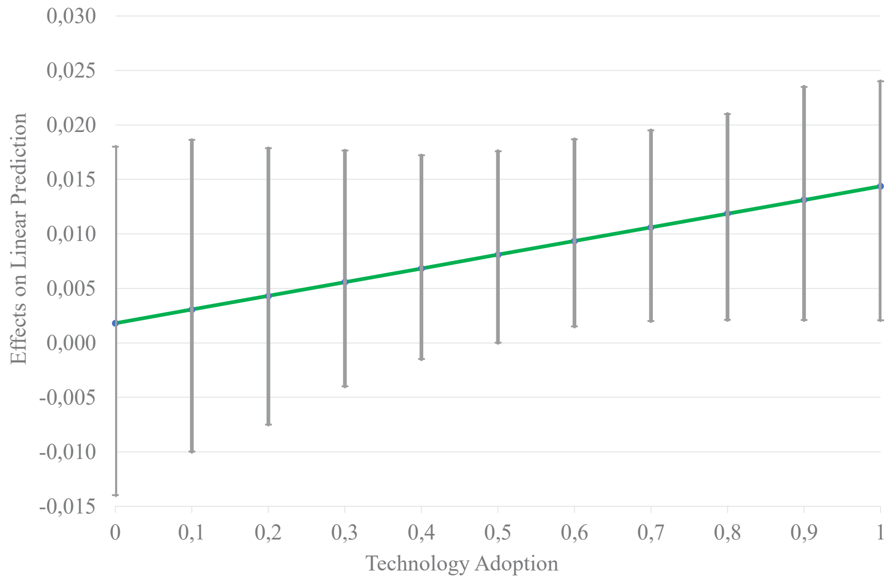
Table 2 – Regional reindustrialization patterns, technological adoption, and productivity growth

	(1) prod growth ind	*(2) prod growth ind*	*(3) prod growth ind*	*(4) prod growth ind*	*(5) prod growth ind*	*(6) prod growth ind*	*(7) prod growth ind*	*(8) prod growth agg*
reindustriali-zation	0.008*	0.002						
	(0.005)	(0.009)						
reinforcement			0.011*	0.018***	0.011*	0.011*	0.010*	-0.004
			(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
shrinkage			0.009*	0.009*	0.007	0.009*	0.009*	-0.004
			(0.005)	(0.004)	(0.008)	(0.005)	(0.005)	(0.004)
diversification			0.005	0.006	0.005	0.002	0.004	-0.006
			(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.005)
enlargement			0.007	0.007	0.007	0.007	-0.004	-0.009
			(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
tech	-0.007	-0.017	-0.007	-0.003	-0.007	-0.008	-0.012	-0.006
	(0.007)	(0.012)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.004)
tech* reindus-trialization		0.013						
		(0.013)						
tech* reinforcement				-0.020				
				(0.015)				
tech* shrinkage					0.003			
					(0.010)			
tech* diversification						0.009		
						(0.008)		
tech* enlargement							0.020**	0.010**
							(0.010)	(0.004)
hc secondary	0.026*	0.024*	0.026**	0.026*	0.026*	0.026**	0.025*	0.048***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)
hc tertiary	-0.026	-0.025	-0.024	-0.025	-0.024	-0.024	-0.024	0.040***
	(0.038)	(0.039)	(0.037)	(0.038)	(0.037)	(0.037)	(0.038)	(0.012)
R&D	0.006***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
city over mln	0.007*	0.007	0.006	0.006	0.006	0.006	0.007	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
gdp pc	-0.649**	-0.639**	-0.601**	-0.592**	-0.600**	-0.587**	-0.607**	-0.502***
	(0.252)	(0.259)	(0.285)	(0.272)	(0.288)	(0.284)	(0.274)	(0.132)
constant	0.007	0.013	0.005	0.004	0.006	0.006	0.009	-0.010
	(0.007)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.011)
No. of obs.	237	237	237	237	237	237	237	237
R2	0.140	0.146	0.148	0.162	0.148	0.151	0.166	0.321
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Robust standard errors are clustered by country. Significance levels as follows: *** 1%, ** 5%, * 10%.

Source: Authors' elaboration

*Figure 1 – Average marginal effects of reindustrialization on industrial productivity gains for increasing values of technology adoption**



Note: (*) confidence interval at 90%.
Source: Authors' elaboration

patterns, so as to test whether there are in fact differences in the relationship between distinct reindustrialization patterns and industrial productivity growth.

In this sense, column (3) in Table 2 shows how, as expected, regions reindustrializing according to a *reinforcement* or a *shrinkage* pattern (those modes implying an increased specialization) are characterized by a better performance with respect to non-reindustrializing ones. This is probably due to *strengthened competitiveness mechanisms*, operating through the intensification of the specific know-how and collective learning processes in regions in which the reindustrializing sectors are particularly *rooted in the territory*. Also in this case, some possible propagation effects are detectable, since specific regional reindustrialization patterns are associated with productivity growth in the whole industry. On the other hand, regional reindustrialization patterns associated with a higher degree of diversification do not reach a critical mass that would favor productivity gains, missing any cumulative self-reinforcing processes of local knowledge.

To dig further into our research interest, we test the role of technological adoption in reindustrializing sectors in enhancing the linkage between reindustrialization patterns and productivity gains. In particular, we aim at investigating if this relationship depends also on the type of reindustrialisation processes, and not only on the mass of firms involved in modernization processes present in the sectors. For this reason, the relationship of different types of reindustrializing regions with industrial productivity dynamics through technological transformation processes is specifically investigated (Table 2, Columns 4-7).

Looking at the interaction terms between regional reindustrialization patterns and technology adoption, the most impressive result comes from the *enlargement* reindustrialization pattern (Column 7 in Table 2). In this case, the interaction between 4.0 technology and the dummy variable for the regions associated to this particular pattern is positive and statistically significant in its propagated effect on industrial productivity growth. This may be also due to a higher number of inter-industrial linkages that can be activated in this specific case, which in fact implies a higher degree of heterogeneity in the reindustrializing manufacturing sectors. As expected, this type of reindustrialization needs to be associated to technological adoption if one wants to achieve productivity gains. Interestingly enough, this result is apparent even when we use real *aggregate* regional productivity growth as the dependent variable (Column 8 in Table 2), showing how powerful the propagation of the detected effects is. In this sense, it seems that an effective modernization within trend of enlargement of sectors through regional reindustrialization does indeed activate favorable inter-sectoral spillovers, also towards (business) services. Such positive effects do eventually propagate even at the aggregate regional level.

As for the other variables included in this last specification, we can instead notice how the *reinforcement* and *shrinkage* reindustrialization types are not significant anymore, since their effect seems to be not strong enough to be significantly linked to the dynamic of aggregate productivity. Human capital in terms of tertiary education becomes extremely significant, confirming that – although not really relevant in the industrial sector – a high-level human capital is in fact a strong determinant of regional performance. R&D is instead not significant in this specification, but this is due to the prevailing role of high-level human capital in this particular model.[13] Moreover, urbanization economies – measured through the presence of large cities – become statistically significant in this model and the coefficient associated with GDP per capita further increases its statistical significance.

In all other cases (Columns 4-6), there seems to be no synergy between reindustrialization patterns and technology adoption, witnessed by the non-significant coefficient of the interacted term. This was mostly expected, since the critical mass associated with the *reinforcement* and the *shrinkage* reindustrialization

13. In fact, high-level human capital and R&D are correlated. By removing human capital from the regression, R&D turns out to be statistically significant again.

patterns, in terms of accumulated know-how, collective learning processes, and importance of the reindustrializing sectors, implies that basically they are already quite efficient and in fact do not really need to modernize. As for the *diversification* pattern, although the result was not really anticipated, it could well be the case that a longer time span is needed to see some significant outcome.

Overall, it is important to consider that a longer time frame is likely to be needed in order to better appreciate and assess the effects of different modes of reindustrialization, as well as of technological transformations, in terms of productivity dynamics. More specifically, in the case of technological transformations we also need to take into account that, to be really effective, a relatively lengthy time horizon may be necessary, since process innovation should be accompanied by related organizational innovation (Brynjolfsson *et al*., 2017; Brynjolfsson, Hitt, 2000; Chaminade *et al*., 2018). In fact, it is not "simply" a matter of replacing one worker with one machine, but the restructuring of a whole procedure is necessary (Brynjolfsson, McAfee, 2014). A strategic use of automation requires indeed imagination, great organizational competence in managing transformations, flexibility, and entrepreneurial skills (Szalavetz, 2019; Capello, Lenzi, 2022), since it entails the simultaneous renewal of processes and delivery chains and the elimination of outdated technologies, processes, and business models (Martinsuo, Chaoji, 2017). Admittedly, these processes are not easy to pursue and guide and all these elements take time to develop. Therefore, the effects on the statistics of productivity dynamics may need a long while to be visible. This reasoning can be even more relevant when reindustrialization patterns that imply a higher degree of diversification are involved. In these cases, in fact, it may well be that initially the costs of diversification could somehow prevail, while the related gains may take longer to manifest themselves.

5. Conclusions

The present work carried out an in-depth reflection on the way in which the adoption of new technologies in reindustrialization processes can be linked to a productivity relaunch in Europe. Our approach is based on a clear territorial perspective and our findings highlighted that reindustrialization patterns associated with a strong and strengthening know-how are positively related with industrial productivity growth, mainly because of their critical mass.

Effective technological transformations become instead necessary in order to establish a clear linkage between productivity dynamics and a regional reindustrialization based on a radically new behavior in terms of *enlargement of the pre-existing diversified industrial fabric*. In fact, through technological progress and organizational and managerial innovation that open to local production excellence, a relaunch of the local economy can be possible even in these cases. This is true independently from the specific manufacturing sectors involved, and therefore this occurrence does not have to be associated with science-based fields and high-tech giants, but can be applicable even to low-tech contexts in which there may be a prevalence of SMEs. What matters is indeed the mode through which a region reindustrializes and not its industrial composition in terms of high- vs. low-tech domains.

From the outcomes of the work, a demand clearly emerges in terms of policy suggestions, to try and understand what sort of strategies and policies are needed and most effective to revitalize the manufacturing sector of the advanced economies.

Building on (and strengthening) the existing knowledge may well be a valid starting point. However, this work showed that a modernization which is not strictly based on R&D and (high-tech) sectoral composition is also an extremely relevant element in order to pursue a relaunch of productivity growth. In this sense, we should avoid the already mentioned "high-tech myopia", considering instead how important a wider range of process and organizational innovations can be. Even low-tech sectors, which are not necessarily characterized by a low level of innovation, could well contribute to a modern European reindustrialization trend through the adoption and adaptation of new technologies (Mendonça, 2009).

Related to this, classical high-level human capital is vital to manufacturing in general, but it is somehow less relevant for traditional sectors (Hansen, Winther, 2014). In this sense, a need of more technical competences has definitely appeared. Thus, and in some way in contrast to the main focus of the literature, it is important that the image and quality of vocational education is enhanced in order to attract and educate students with both academic and practical skills.

Of course, we should be aware that technological change can negatively impact those occupations characterized by routine tasks[14], which can be easily outsourced or automatized. This type of process can be for sure compatible with labor productivity growth. Related to this, we may think that an effective industrial policy should consider the technological content, but also the workforce absorption capacity. Therefore, deepening the understanding of the mechanisms behind the relationship between technological transformations and productivity dynamics is an important topic for future research.

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Processi di trasformazione regionale: reindustrializzazione e aggiornamento tecnologico come fattori di incremento della produttività

Sommario

La reindustrializzazione è una delle trasformazioni che ci si aspetta dalle economie europee. È stata infatti suggerita dalle istituzioni politiche europee come una delle strategie per contrastare la stagnazione della produttività che si è verificata negli ultimi 20-30 anni. Tuttavia, ciò che le istituzioni europee caldeggiano è una reindustrializzazione moderna, che avvenga attraverso progresso e trasformazione tecnologica. Questo capitolo contribuisce al dibattito sostenendo che l'adozione di nuove tecnologie 4.0 nei processi di reindustrializzazione (ad esempio l'automazione digitale nel settore manifatturiero) sia fondamentale al fine di conseguire guadagni di produttività. Questo è vero specialmente quando la reindustrializzazione avviene in aree in cui una varietà diversificata di settori locali non genera una massa critica di know-how sulla base della quale le imprese possono eccellere e competere. E ciò si applica sia ai settori avanzati sia a quelli tradizionali, secondo una logica che vede con favore il ruolo che può essere svolto dai settori low-tech nel rilanciare la produttività rispetto ai giganti dell'high-tech, solitamente considerati. Il capitolo presenta evidenza empirica a questo riguardo, grazie ad una banca dati originale su occupazione e valore aggiunto a livello regionale (NUTS2) nei sottosettori manifatturieri nei paesi membri dell'UE, più il Regno Unito. I risultati mostrano che, mentre una reindustrializzazione improntata su settori di specializzazione conduce a incrementi di produttività indipendenti dai livelli di adozione di tecnologie 4.0 in quei settori, una reindustrializzazione che interessa una varietà di settori locali favorisce la crescita della produttività solo se tali settori sono caratterizzati da importanti avanzamenti tecnologici.

Annex

Data

For the first step of the analysis, i.e. the operational identification of reindustrializing NUTS2 regions in Europe, the main data source for *total and manufacturing VA at current prices*[15] is Eurostat table [nama_10r_3gva]. Missing data for France were retrieved from the French Statistical Office (INSEE) and, due to some discrepancies between the sum of Eurostat regional (NUTS2) data and Eurostat national (NUTS0) data, regional data were reproportioned based on national data (such reproportioning was subsequently carried out for any data used, in order to achieve perfect consistency between every phase of the analysis)[16].

For the second step of the research, i.e. the identification of the different regional patterns of reindustrialization, due to the need of more sectorally disaggregated regional data, the information was mainly collected through the interaction with the individual European National Statistical Offices (NSOs). When such data were not available, the necessary pieces of information were estimated assuming that the regionally reindustrializing manufacturing sectors were those reindustrializing at the national level (data available from Eurostat) and, to compute the indicator of specialization (LQ) in the two periods, national data were regionalized according to the regional-sectoral distribution provided by the IGEAT (University of Brussels) matrix, which includes NACE 2-digit level sectoral information for all regions of the EU in 1995, 2002, 2004 (pre-crisis) and 2014 (post-crisis)[17].

Due to differences in the sub-manufacturing sectoral aggregation provided by the NSOs, in order to have a homogeneous and comparable European regional database we ended up with 9 manufacturing sectors, namely:

- CA – Manufacture of food products, beverages and tobacco products (10-12);

15. In this work, reindustrialization occurs when the change in the share of current manufacturing VA in a post-crisis period (2013-2017) is higher than the change in the share of current manufacturing VA in a pre-crisis period (2000-2007).The share, rather than the absolute value, guarantees that the price effects are controlled for, while the VA at current prices contains the quality effect (see Capello, Cerisola, 2022).

16. Ireland was excluded from the analysis due to a "jump" in the VA data during the post-crisis period (2013-2017) that would generate biased estimates and an incorrect comparison with the pre-crisis period (2000-2007).

17. This was the case for Greece, Netherland, Poland, Portugal, and Sweden. The same estimation method was used for Bulgaria and Germany only for the first period, while Croatia, Lithuania and Slovenia were kept at NUTS0 level. Luxembourg is not included in this step of the analysis due to lack of consistent data. Finally, France is a special case where the NSO manufacturing data were provided aggregated into only 5 sectors, which – when needed – were disaggregated into our 9 sectors through the IGEAT matrix.

- CB – Manufacture of textiles, apparel, leather and related products (13-15);
- CC – Manufacture of wood and paper products, and printing (16-18);
- CD-CE-CF – Manufacture of coke, and refined petroleum products (19); Manufacture of chemicals and chemical products (20); Manufacture of pharmaceuticals, medicinal, chemical and botanical products (21);
- CG – Manufacture of rubber and plastics products, and other non-metallic mineral products (22-23);
- CH – Manufacture of basic metals and fabricated metal products, except machinery and equipment (24-25);
- CI-CJ-CK – Manufacture of computer, electronic and optical products (26); Manufacture of electrical equipment (27); Manufacture of machinery and equipment n.e.c. (28);
- CL – Manufacture of transport equipment (29-30);
- CM – Other manufacturing, and repair and installation of machinery and equipment (31-33).

Relative Prices

Table A1 – Trend in Relative Prices 2000-2017 in the EU28

Manufacturing prices/total prices in the EU												
2000	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2013*	*2014*	*2015*	*2016*	*2017*
1.142	1.125	1.108	1.084	1.061	1.046	1.019	1.012	1.002	0.994	1.006	1.009	1.006

Source: authors' elaboration on EU KLEMS data

As can be inferred from Table/Figure A1 above, for the second period, the ratio is relatively stable and therefore prices do not influence our share of manufacturing VA. In the first period, instead, the ratio decreases, witnessing that service prices increased more than manufacturing ones and influence the trend in the share of manufacturing VA. In relative terms, the quality in manufacturing increases less than the one in services, which is in fact a signal of loss of competitiveness, consistent with a deindustrialization process, which was actually taking place in the period. The trends in service prices only emphasize such a tendency.

Circular Economy Transition and Recombinant Dynamics in European Regions: The Role of Localized Knowledge and Digital Technological Complementarities

Fabrizio Fusillo, Francesco Quatraro**

Abstract

A sustainable transition is one of the most important challenges Europe is facing. Such transition imposes an urgent need to move toward a Circular Economy (CE), calling for a deeper understanding of the relationship between innovation, technologies, and CE, which received relatively less attention in existing literature, particularly at the regional scale. This chapter contributes this debate by investigating regional recombinant dynamics in CE technologies, focusing on the role of localized knowledge, accumulated green capabilities, and the interplay with digital complementary technologies. The empirical analysis is conducted on a dataset of European NUTS2 regions over the period 1985-2015 and suggests that green and digital complementary localized capabilities increase the regional ability to absorb and integrate new technological opportunities in CE-based recombinations, representing a crucial leverage for stimulating regional transition.

1. Introduction[1]

The challenges posed by the negative consequences of climate change require collective actions aimed at reducing the environmental burden of human activities

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and favoring the transition of local economic systems to sustainable models of production and consumption. In this context, the Circular Economy paradigm has been proposed as the most promising framework to achieve the decoupling of economic development from the exploitation of limited resources (Sauvé, Bernard, Sloan, 2016; Bibas, Chateau, Lanzi, 2021). The so-called Circular Economy (CE) transition received increasing governmental support around the world to mitigate environmental pressure on the one hand and promote economic development, entrepreneurship, and employment on the other hand. The European Circular Economy Action Plan confirmed the centrality of CE in the industrial and climate policy at the European level by introducing measures and incentives to support waste management and prevention, eco-design, and markets for secondary raw materials. In order to feed the CE transition, the Action Plan acknowledges the central role of innovation and digital technologies as already recognized in the Policies and practices for the adoption of eco-innovation and the transition to the Circular Economy (EIO, 2016). As a result, academic literature has recently begun to investigate to what extent the digital transformation can increase the chances of achieving an innovation-based sustainable transition. Indeed, digital technologies can help unlock cuts in carbon emissions, increase the use of renewables and improve energy and material efficiency, thus promoting a circular economy development model. Accordingly, the label of "twin transition" has come to the fore and gained momentum in both political and academic contexts to emphasize the relevance of this phenomenon (Montresor, Quatraro, 2017; Santoalha, Consoli, Castellacci, 2021; Cicerone *et al*., 2022).

Nevertheless, the scant evidence on the interaction between the CE and innovation dynamics (Jakobsen *et al*., 2021) has mainly focused on individual technologies in specific CE-related domains (Barragàn-Ocaña *et al*., 2021) or on providing a mapping of the regional innovative efforts across the full spectrum of CE technologies, describing the main actors involved, the main technological trajectories and geographical heterogeneity (Fusillo *et al*., 2021). Yet, the regional recombinant dynamics around CE technologies remained largely unexplored.

This chapter contributes to filling this gap by studying the local recombinant dynamics behind the integration of CE knowledge and the role of existing local green and digital knowledge endowments in this regard. By opening the black box of CE-related local recombinant dynamics, this chapter makes a step forward in the understanding of such mechanisms and investigates the role of regional technological capabilities in influencing the ability to absorb and integrate new technological opportunities in the CE field. We provide evidence of the instrumental role of green knowledge in supporting the integration and exploitation of new CE recombination opportunities. Further, we delve into the crucial role of digital technologies and the exploitation of digital complementarities for recombinant regional capacities, contributing to the debate on the interaction between the sustainable and digital transformation. Lastly, we provide additional evidence on the positive effects of cognitively related knowledge bases and the regional characteristics that may complement or substitute technological relatedness. Drawing upon the literature on regional branching, we also show if and to what extent the endowment of complementary digital technologies could attenuate the stickiness of local capabilities.

Leveraging the OECD REGPAT patent database, we construct a dataset of European NUTS-2 regions observed in the period 1980-2015. The empirical analysis focuses on the regional stock of CE-technological recombination in patent citations and builds an original indicator of digital technological complementarity, together with localized knowledge endowments in the green and digital technology fields. Our results show that localized knowledge is positively associated with the recombinant capabilities of regions around CE technologies. In particular, we find that complementary digital technologies play a prominent role, suggesting that CE technologies contribute to the development of new knowledge and that their complementarity with digital technologies is functional to stimulate regional recombination activities. Our findings also show that the relatedness between CE technologies and the regional knowledge base is positively associated with CE recombinations and that complementary digital knowledge negatively moderates such relationship.

The chapter is organized as follows. Section 2 summarizes the relevant literature and introduces the conceptual framework. Section 3 presents the data and the methodology used, while empirical results are presented in Section 4. Section 5 summarizes the main findings and concludes.

2. CE, Local Recombinant Capabilities and Digital Complementarities

The CE paradigm is gaining ground as a strategy to make existing production and consumption activities more sustainable (Geissdoerfer *et al.*, 2017). Indeed, the CE approach introduces closed resource loops to separate economic growth from finite resource consumption (Korhonen *et al.*, 2018). It opposes the predominant linear model, based on the pattern "take-make-use-dispose", which has led to volumes of resource extraction and waste production beyond the Earth's regeneration and absorbing capacity (Murray *et al.*, 2017). The CE seeks to maintain the value of products, materials, and resources for as long as possible in the economy by extending their useful life and reintroducing them in the production cycle at the end of their life (Rosa *et al.*, 2019). Following the seminal work of Stahel (1994), the reuse of goods and the recycling of materials have been addressed by scholars as the foremost waste-reduction and resource-saving strategies. The former allows for the extension of the useful life of products and delays the disposal of materials, namely the *slowing* resource loop. At the same time, the latter makes the recovery of resources possible, thus *closing* resource loops (Stahel, 1994). Efficiency strategies that result in the reduction of raw materials or energy employed in an item's production, transportation, and utilization phase ultimately allow for minimizing resource consumption, hence narrowing the resource flow (Geissdoerfer *et al*., 2017).

To realize its full potential, the CE calls for a systemic change in companies, industries, and the economy through radical shifts in societal values, norms, and behaviors (Chizaryfard *et al*., 2021; Murray *et al*., 2017). In this scenario, industrial and regional systems are expected to encompass radical and systemic innovation to search for innovative and creative solutions, such as cleaner technologies, business models, infrastructures, and institutional capacity (Chizaryfard *et al*., 2021). Thus, a successful transition from a linear to a circular organization of economic activities calls for a comprehensive understanding of the relationship between innovation and CE implementation. However, despite the crucial role of innovation in designing and implementing CE practices, "the term CE is relatively absent from the innovation literature" (Jakobsen *et al*., 2021, pg. 4). The first attempt to establish a direct link between innovation and CE is represented by Jakobsen *et al*. (2021), which highlighted the "potential in applying insights from the innovation literature to provide more specific implications for how to implement the transition from a linear to a CE." (Jakobsen *et al*., 2021, pg. 4). Existing quantitative research has mostly provided insights into the evolution of single technologies applied in specific CE-related domains. Barragán-Ocaña *et al*. (2021), exploiting patent data, sought to identify the technological trajectory of wastewater reuse technologies. A study with a similar approach targeting a broader sample of CE technologies is provided by Fusillo *et al*. (2021), which map CE innovative efforts describing the main actors involved and the key technological trajectories. Yet, in this panorama, the determinants of CE technologies and the recombinant dynamics exploiting CE-related knowledge remain largely unexplored (Cainelli *et al*., 2020; de Jesus *et al*., 2018), particularly in the regional context. Cainelli *et al*. (2020) point to the role of environmental policy and green demand in driving the adoption of resource efficiency-oriented eco-innovations at the European level. However, the role on the technological background and the regional capabilities that favor the recombination of knowledge in the CE field has not been investigated yet.

Following the recombinant knowledge framework, innovation is the outcome of recombination processes, involving the novel combination of existing ideas, information, or technological components (Arthur, 2009; Kauffman, 1993; Schumpeter, 1939; Weitzman, 1998). From an evolutionary perspective, recombinant dynamics incorporate technological improvements along several paths, speeding up technical progress and sustaining technological transitions (Frenken *et al*., 2012). Limited access to knowledge sources, risk aversion, and other organizational impediments may constrain the search process through existing know-how and narrow the possibility to develop new technological knowledge (Fleming, 2001). In this context, recombinant capabilities concern the capacity of individuals to access external knowledge and to successfully manage novel recombinations (Carnabuci, Operti, 2013).

Extant geography of innovation literature has proposed the extension of the concept of innovation capabilities at the regional domain, to denote the capacity of institutions and local agents to master and coordinate systemic interactions to produce new knowledge (Cooke, 2001; Lawson, Lorenz, 1999; Quatraro, 2009; Romijn, Albu, 2002). Regional innovation capabilities are the outcome of localized knowledge interactions and exchange activities among local agents that trigger the accumulation of skills and knowledge through learning dynamics (Antonelli, 1998; Freeman *et al*., 1987). This introduces both path and place-dependent processes based on the exploitation of technological capabilities accumulated in local contexts to absorb and integrate new technological opportunities (Cohen, Levinthal, 1990; Colombelli *et al*., 2014; Henning *et al*., 2013; Martin, Sunley, 2006; Storper, 2018). Following this approach, the concept of regional recombinant capabilities has recently been proposed to indicate the ability of local innovation ecosystems to stimulate combinatorial efforts leading to the introduction of novelty (Orsatti *et al*., 2021).

Acknowledging the path-dependent dynamics of regional recombinant capabilities provides a fertile ground for the analysis of local innovation processes in the CE domain. In this direction, the extant literature allows for the identification of three main enabling channels influencing the capacity to engage in CE-based recombinations at the local level, i.e., green technological capabilities, digital complementarities, and technological relatedness. For what concerns green technological capabilities, extant literature has stressed the impact of previous experience in green innovation dynamics for the further generation of novelties in this domain (Orsatti *et al*., 2020). In the context of CE-related technological change, de Jesus *et al*. (2018) have stressed the instrumental role of environmental innovation (EI) in achieving the CE objectives. More recently, microeconomic evidence has shown that CE solutions appear to depend more on existing technologies that address systemic innovations rather than on radical innovations. Moreover, a firm's technological capabilities and knowledge sourcing from diverse networks have proven to be essential in fostering the production of circular eco-innovation and creating a competitive advantage (Demirel, Danisman, 2019; Kiefer *et al*., 2021; Triguero *et al*., 2022). In this direction, established capabilities in green technological change can be a source of competitive advantage in CE-based recombinations, in view of their reliance on diversified knowledge bases stemming from the integration of diverse and heterogeneous knowledge sources, requiring different and heterogeneous technology fields and skills (Barbieri *et al*., 2021; De Marchi, 2012; Fusillo, 2020; Fusillo *et al*., 2022; Petruzzelli *et al*., 2011). Based on this discussion, we hypothesize that the extent to which regions are able to integrate and exploit new recombination opportunities in the CE field depends on the technological capabilities in the green domain accumulated within regional knowledge bases.

Extant literature also pointed to digital technologies as essential enablers of circular innovation and practices implementation within businesses (Bag *et al*., 2020; Chauhan *et al*., 2022; Ranta *et al*., 2021). The European Eco-Innovation Observatory has first recognized the importance of EI in carrying out the transition from a linear to a circular economic system (EIO, 2016) and, more recently, the role of digitalization and artificial intelligence as an accelerator of energy and resource optimization (EIO, 2021). Digital technologies are critical to manage the increasing amount of knowledge and information flows captured and transferred among companies, to track products and materials, and, ultimately, to improve the efficiency of production and distribution processes (Salvador *et al*., 2021). Pagoropoulos, Pigosso, and McAloone (2017) illustrate the grouping of digital technologies in three classes based on their function: data collection, data integration, and data analysis. Data collection technologies include sensors (e.g., radio frequency identification) and devices that connect products and users to the Internet (e.g., the Internet of things). These technologies are crucial to reveal inefficiencies in extant business models and production methods and, thereby, support the production process optimization and the value chain management (Ranta *et al*., 2021). Data integration and data analysis technologies (e.g., Artificial Intelligence (AI) tools and techniques or Big Data analytics) format and process huge amount of data to provide information (Pagoropoulos *et al*., 2017). Digital technologies play a key role in driving the shift toward novel business models, such as hybrid product–service solutions (PSS) and pay-per-usage models (Chauhan *et al*., 2022; Pagoropoulos *et al*., 2017). Indeed, IoT technologies gather data and inform the owner on the location and maintenance status of a set of items. The ability to track the connected items ease the access from a multitude of users, and data collected are employed to improve their durability, preventing premature breakdowns, and thus slowing resource flows. The digitalized systems are finding more and more applications also in the waste management sector, crucial to achieve CE objectives, in form of sensors for material detection or robotic technologies for sorting of mixed waste (Sarc *et al*., 2019).

Because of their enabling role and their broad applicability across domains, digital technologies and AI are assimilated to General Purpose Technology (GPT) (Trajtenberg, 2019). GPT have been found to widen the scope for knowledge search and move the technological frontier, allowing local systems to exploit complementarities across knowledge domains and introduce new and unprecedented recombinations (Bresnahan, Trajtenberg, 1995; Capello, Lenzi, 2021). Regional scholars have widely confirmed the role of GPTs and their new generation, i.e., the Key Enabling Technologies (KETs), on the regional ability to open new technological diversification paths (Montresor, Quatraro, 2017). The local endowment of KETs in general, and of AI in particular, has been also found to increase the likelihood of regional technological diversification in the green domain (Montresor, Quatraro, 2020), though AI seems to favor regions already possessing sound green technological specializations (Cicerone *et al*., 2022). These considerations suggest that the transition to a circular economy could greatly benefit from the potentiality of digital technologies to integrate multiple and technologically dispersed knowledge bits. Accordingly, the localized endowment of digital technologies can be seen as promising tools to foster recombinant dynamics leveraging on CE-related technologies. Yet, the wide spectrum of digital technologies may reveal high differences in the extent to which they connect knowledge bases and favor successful recombination (Martinelli *et al*., 2021). Circular strategies rely on timely and effective data management and sharing, the optimization of energy and material usage in both the production and utilization phase, the management of forward and reverse logistics. Thus, technologies for data collection, storage and processing, and digital communication may provide regions with specific but complementary digital capabilities instrumental to the absorption and recombination of new CE-related knowledge. The role of complementary capabilities is gaining increasing attention in technology and regional studies. For example, complementary capabilities have been shown to play a key role in preventing regions from ending up in a lock-in situation (Balland, Boschma, 2021a). Balland and Boschma (2021a) further argue that a new technology has a higher probability to enter a region when the latter has access to complementary capabilities for this new technology provided by other regions. By focusing on green technologies, Barbieri *et al*. (2021) shows that their development also depends on improvements in non-green but complementary technological areas. Along these lines, we hypothesize that localized cumulated knowledge in digital complementary technologies allow regions to integrate new technological opportunities within knowledge bases, favoring regional recombinant capabilities around CE-related knowledge.

Finally, evolutionary economic geography literature recognizes technological relatedness as another key driver for the success of new knowledge recombinations (Balland *et al*., 2019; Boschma, 2017). According to the relatedness framework, the recombination of knowledge is more likely to take place the more the components are related to each other from a technological perspective (Neffke *et al*., 2011; Tanner, 2014). This suggests that knowledge recombination is shaped by the similarity between pre-existing local knowledge base and the new technological knowledge.

Accordingly, high levels of cognitive proximity between the extant knowledge bases and the new technological knowledge may increase the absorptive capacity and ease the assimilation of such new knowledge. Recent contributions highlighted the importance of relatedness in sustaining regional specialization in specific technological domains, such as renewable energy (Moreno, Ocampo-Corrales, 2022). Within the European landscape Santoalha and Boschma (2021) show that new specializations in green technologies are more likely to occur in regions with related technologies. Perruchas, Consoli, and Barbieri (2020) obtained similar results on a worldwide sample at the country level. Montresor and Quatraro (2020) add that the regional entry of new green technologies is driven by the relatedness to the pre-existing technologies that are both green and non-green. Balland and Boschma (2021b) and Corradini, Santini, and Vecciolini (2021) find that the knowledge around industry 4.0 technologies (I4T) is more likely to thrive in regions with local capabilities in I4T- related technologies. Based on this background, we expect that regions endowed with pre-existing knowledge bases related to the CE technological domain are better able to integrate new knowledge based on CE-related technological advancements into their recombinant innovation activities.

Building on the relatedness framework, an emerging body of research identified a broad set of regional factors that may substitute or complement the role of relatedness (Castellani *et al*., 2022; He, *et al*., 2018; Montresor, Quatraro, 2017). These factors may attenuate the cognitive constraints that being close to the existing knowledge base may pose to the recombination and development of new and/or unrelated technologies (Elekes *et al*., 2019; Miguelez, Moreno, 2018; Neffke *et al*., 2018; Zhu *et al*., 2017). Because of the enabling role of digital capabilities to connect distant but complementary knowledge domains and ease the exploitation of recombination opportunities, digital complementary capabilities could hinder lock-in effects triggered by related paths, enabling regions to overcome the stickiness of local capabilities. Thus, we expect that the local endowment of digital complementary cumulated knowledge negatively moderates the constraining role of CE technological relatedness. In other words, larger stocks of digital complementary knowledge provide regions with an asset allowing CE-related recombinant dynamics to span areas of the technology landscape that are loosely related cognitively to one another.

3. Empirical Analysis

3.1. Circular Economy Technologies

In order to investigate the knowledge recombination dynamics of CE technologies, we exploit patent data extracted from the OECD REGPAT database, March 2020, collecting information on patent applications at the European Patent Office (EPO) published between 1980 and 2015. We also make use of the OECD Citation Database, March 2020, to retrieve all the citations in the EPO and PCT patent documents.[2]

Relying on the well-grounded and widely accepted classification provided by the European Commission, we first identify patents related to the CE. Precisely, the EC provides a list of technological classes, following the Cooperative Patent Classification (CPC) code, in the set of Circular Economy indicators to monitor progress toward a circular economy on the thematic area of competitiveness and innovation.[3] The list encompasses technological codes belonging to the subclass Y02W on "Climate change mitigation technologies related to wastewater treatment or waste management". Accordingly, we classify as Circular Economy related those patents assigned to at least one of these technology fields. Thus, in line with recent literature, the focus is on the development of techniques for the collection, reduction, and recycling of waste, water, and materials aimed at reducing the dependence on critical commodities while improving economic resilience (Cainelli *et al*., 2020). The identified set of CE patents consists of 6,407 patents from 1980 to 2015, for which at least one inventor resides in a European country. Inventors' addresses, provided at NUTS2 regional level, have also been used to assign patents to regions and measure their inventive activity. For co-invented patents with listed inventors residing in multiple regions, patent applications are proportionally allocated to regions applying fractional counting.

3.2. Variables and Methodology

The set of identified CE-related patents is employed to build the dependent variable. Our dependent variable is, thus, a measure of the regional stock of CE-related knowledge recombination. Precisely, considering the purpose of our analysis and the still limited number of CE patents, we measure CE recombinations by counting the number of patents that cite at least one circular patent in the backward citations of a region's patenting portfolio. To avoid year-to-year fluctuations in the number of patents and account for the cumulated knowledge, providing a deeper insight into the phenomenon at stake, we make use of a stock variable. The stock of CE knowledge recombinations (*CE recomb*) is computed

2. It is worth stressing that, notwithstanding the well-known drawbacks in the use patent data (Griliches, 1998), they are one of the most effective sources to explore regional inventive activities as they provide a wealth of granular information on the location, time, and technologies of such activities (Jaffe, Trajtenberg, 2002; Strumsky *et al*., 2012).

3. The European Commission CE monitoring framework is available at ec.europa.eu/eurostat/web/circular-economy.

using the perpetual inventory method (PIM), calculated as the cumulative stock of CE citing patents by region, applying a yearly rate of obsolescence of 15%.[4]

Our first explanatory variable is the overall regional knowledge stock (*K Stock*) that accounts for the region's absorptive capacity and is expected to affect the ability of regions to recombine CE technologies. The regional stock of knowledge is calculated by applying the PIM method to the whole regions' patent portfolios. Secondly, to account for the localized endowment of green and digital technological capabilities two independent variables are built. As for the former, the cumulated know-how in the green technological domain is measured as the stock of patents with at least one backward citation toward green patents (*GT Stock*). Green-tech patents are identified following the OECD ENV-TECH classification (Haščič, Migotto, 2015), which provides the list of technological classification codes associated to the environmental domain based on the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).[5] Concerning the cumulated localized knowledge in the digital domain, we classify as digital those patents that are assigned to at least one technology class covered by the electrical engineering area as in the classification proposed by Schmoch (2008). Given our interest in the role of complementary digital capabilities in regions and that we expect the enabling role of digital technologies in the recombination of CE knowledge to be proportional to the extent of complementarity between the two fields, we first calculate the degree of complementarity, for each digital technology, with respect to CE related technologies. To do so, we identify those patents co-classified in both CE and digital technologies and then, for each digital technology, we calculate the relative frequency with which they co-occur in the joint CE-digital patents. Then, the relative co-occurrence frequency, representing our proxy for the degree of complementarity, is employed to compute the stock of patents citing digital patents for each region, which is weighted by the degree of complementarity of the corresponding digital technology (*DG compl Stock*). Table 1 reports a list of the top 10 digital technologies ranked by their degree of complementarity with the CE technologies.

To capture the cognitive proximity between regions' existing technological capabilities and CE-related knowledge, we construct a measure of the CE technological relatedness (*CE rel*). Following consolidated existing literature, to measure CE relatedness we, first, exploit the co-occurrence of 4-digits CPC classes in patent documents to calculate the degree of proximity between each

4. The literature includes several attempts to estimate the patent depreciation rate without conclusive evidence (Pakes, Schankerman, 1979; Schankerman, 1998). In this work, we set the obsolescence rate at 15%, which is the most frequent value employed in the literature (see among others Hall *et al*., 2005; Keller, 2002; McGahan, Silverman, 2006; Nesta, 2008).

5. For the sake of consistency between technological classification, IPC codes are converted into CPC codes by exploiting the concordance tables available at cooperativepatentclassification.org.

Table 1 – Top Digital Complementary Technologies

CPC	*Technology*	*Complementarity*
H01M	Processes or means, e.g., batteries, for the direct conversion of chemical into electrical energy	0.4533
G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes	0.1705
H01J	Electric discharge tubes or discharge lamps	0.1380
H01B	Cables	0.0419
H05K	Printed circuits	0.0379
G06K	Recognition of data	0.0325
G11B	Information storage based on relative movement between record carrier and transducer	0.0257
H05B	Electric heating	0.0257
F21V	Functional features or details of lighting devices or systems thereof	0.0230
G06F	Electric digital data processing	0.0230

Source: Authors' elaboration

technology *s* and *c* at time *t*. We define proximity as the minimum pairwise conditional probability of a region having a Revealed Technology Advantage (RTA) in technology *s* given that it has a specialization (RTA) in another technology *c*. In the second step, we calculate the relatedness density of each technology *s* with respect to all technologies *c* in which region *r* has an RTA. Lastly, we select the technology-specific relatedness by filtering the density value corresponding to the CE technology, thus obtaining a measure of the region *r* average relatedness density around CE-related knowledge.

Our baseline specification focuses on the role of overall localized knowledge (*K Stock*) and is expressed by the following equation:

$$CErecomb_{r,t} = \beta_0 + \beta_1 KStock_{r,t-1} + \beta_2 CErel_{r,t-1} + \beta_3 GDPpc_{r,t-1} + \gamma_r + \delta_t + \epsilon_{r,t} \quad [1]$$

where *r* denotes the region and *t* the time period consisting of 5-years time intervals from 1980 to 2015. *CE rel* is our measure of the CE technological relatedness, and *GDP pc* is the regional gross domestic product (GDP) per capita introduced as a control to account for the level of economic development in a region.[6] Region (γ_r) and time (δ_t) fixed effects are also included in the model to account for region-specific time-invariant unobservables and to adjust for common shocks in the period of analysis. $\epsilon_{r,t}$ is an idiosyncratic error term.

6. GPD and population data are extracted from Eurostat.

In the second specification, the role of the stock of green and digital complementary technologies is estimated (respectively *GT Stock* and *DG compl Stock),* yielding the following model:

$$CErecomb_{r,t} = \beta_0 + \beta_1 GTStock_{r,t-1} + \beta_2 DGcomplStock_{r,t-1} + \\ + \beta_3 CErel_{r,t-1} + \beta_4 GDPpc_{r,t-1} + \gamma_r + \delta_t + \in_{r,t} \quad [2]$$

Lastly, to investigate the moderating role of complementary digital knowledge on CE-specific relatedness in affecting regional CE technological recombinations, we extend model in equation 2 by introducing an interaction term as follows:

$$CErecomb_{r,t} = \beta_0 + \beta_1 GTStock_{r,t-1} + \beta_2 DGStock_{r,t-1} + \beta_3 CErel_{r,t-1} + \\ + \beta_4 DGcomplStock_{r,t-1} * CErel_{r,t-1} + \beta_5 GDPpc,_{rt} + \gamma_r + \delta_t + \in_{r,t} \quad [3]$$

Models in equations 1-3 are estimated by using two-way panel fixed effects regressions estimated using OLS. In all specifications, we apply the natural logarithm transformation to adjust for the skewed distribution of the continuous variables and cluster standard errors at the NUTS2 level to account for heteroskedasticity. We further lag explanatory variables by one period. Summary statistics of the variables employed in the models are reported in Table 2.

4. Results

Figures 1 and 2 offer a graphical visualization of the geographic distribution by NUTS2 regions of, respectively, the stock of CE-based recombinations and the stock of digital complementary technologies, over the period 1980-2015. Regions are colored according to the quintile rank of the distribution, where darker colors indicate higher quintiles. Both figures highlight a heterogeneous distribution across European NUTS2 regions, showing that CE recombinant activities and the cumulated digital complementarity capabilities are more concentrated in Central Europe regions (i.e., Germany, northern Italy, Austria, and southern France) with a marked difference with Eastern European regions.

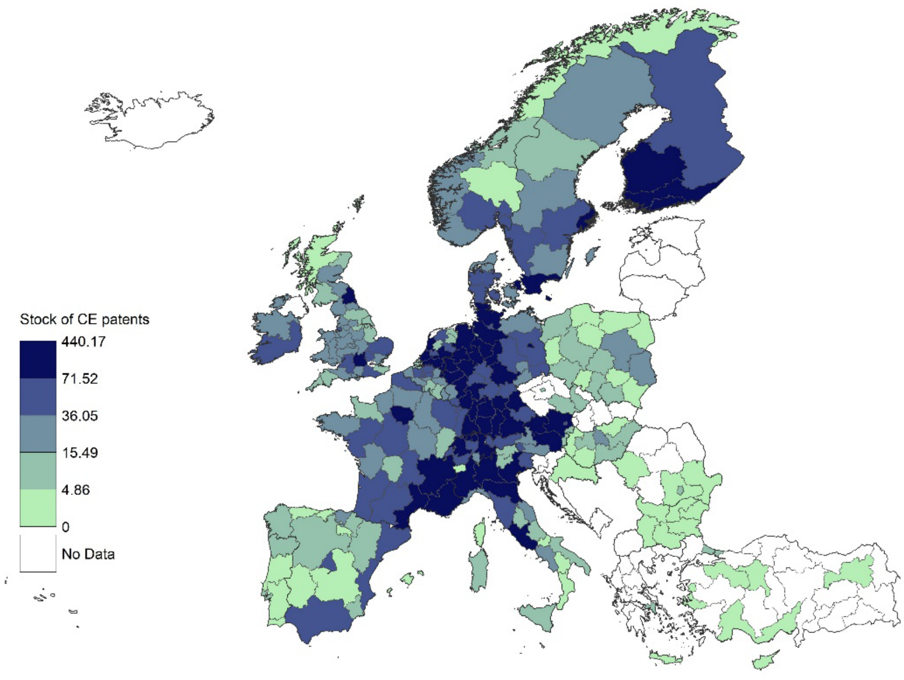
Results of the regression analysis are presented in Tables 3 and 4. Column 1 of Table 3 report the results of our baseline specification where *K Stock* and *CE rel* are the focal regressors. The estimated coefficient of the overall knowledge stock is positive and statistically significant, suggesting that the cumulated regional knowledge capabilities and absorptive capacity are associated with successful recombination dynamics involving CE-related technologies that facilitate the development of new knowledge. Column 1 also shows that the *CE rel* estimated coefficient is positive and significant, suggesting that having technological

Table 2 – Summary Statistics

Statistic	*N.*	*Mean*	*St. Dev.*	*Min*	*Max*
CE recomb	1763	238.790	441.263	0.000	4.401.709
K Stock	1763	21.128.590	46.620.510	0.125	590.953.400
GT Stock	1763	2.979.278	7.350.063	0.000	101.469.600
DG Stock	1763	6.568.777	18.052.360	0.000	240.082.400
DG compl Stock	1763	218.665	601.338	0.000	8.125.498
DG non-compl Stock	1763	6.350.112	17.469.140	0.000	231.956.900
CE rel	1925	0.1600	0.1202	0.000	0.4620
GDPpc	1685	184.667.700	146.655.200	4.528.554	223.603

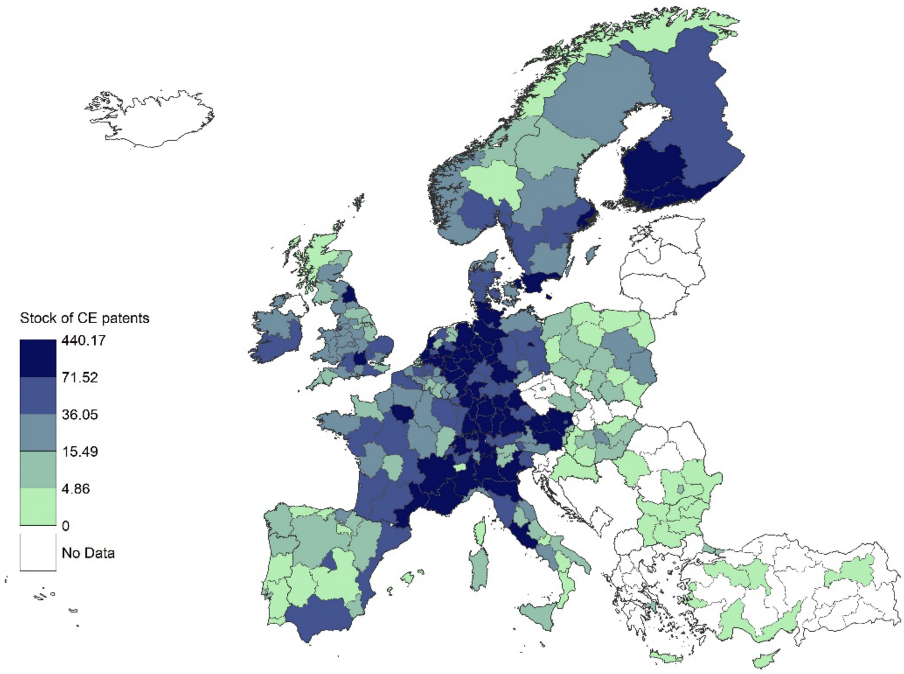
Source: Authors' elaboration

Figure 1 – Geographic distribution of the cumulated stock of CE citing patents by European NUTS2 regions, from 1980 to 2015



Source: Authors' elaboration

Figure 2 – Geographic distribution of the cumulated stock of digital complementary citing patents by European NUTS2 regions, from 1980 to 2015



Source: Authors' elaboration

capabilities in domains related to the CE positively contributes to the recombination of circular knowledge and the generation of new technological knowledge.

Model 2 focuses on the role of localized capabilities in the green and digital domains underlying the contribution of complementary digital technologies. The estimation result presented in column 2 shows that the cumulated know-how in both the green and complementary digital fields is positively associated with regions' ability to develop new technologies leveraging the recombination of the CE-related knowledge. This finding suggests that regions endowed with cumulated capabilities in green and digital complementary technologies are better able to activate positive dynamics of circular knowledge recombination and consequent knowledge creation. Since the knowledge developed within the two fields that characterize the so-called "twin transition" is successfully assimilated and exploited in new technologies developed through the recombination of circular knowledge, this result provides intriguing evidence on the importance of knowledge development progresses to speed up the transition from a linear to a sustainable circular economy model.

Table 3 – CE Recombinations and Localized Knowledge

	-1	*-2*	*-3*
K Stock	0.1669*** (0.0473)		
GT Stock		0.2027*** (0.0438)	0.1680*** (0.0452)
DG compl Stock		0.1468*** (0.0406)	0.3202*** (0.0669)
CE rel	3.9507*** (0.4871)	2.9141*** (0.4624)	3.3805*** (0.4894)
DG compl Stock * CE rel			-0.4877*** (0.1607)
GDPpc	0.1353* (0.0782)	0.2793*** (0.0768)	0.2564*** (0.0748)
Constant	-1.2004* (0.6508)	-2.1019*** (0.6473)	-1.8933*** (0.6291)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
Observations	1,345	1,345	1,345
R^2	0.9678	0.9696	0.9701
Adjusted R^2	0.9605	0.9627	0.9633
F Statistic	1.321.080***	1.397.456***	1.413.745***

Notes: Dep var: regional stock of patents citing CE-related technologies. Explanatory variables are log transformed and lagged by one year. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01.

Source: Authors' elaboration

The hypothesized moderating role of the complementarity between digital and circular technologies on the relationship between CE relatedness and CE recombinant activity is estimated in column 3 of Table 1. The coefficient of the interaction between *DG compl Stock * CE rel* is negative and significant, suggesting that complementary digital capabilities might attenuate the importance of CE relatedness. If, on the one hand, the recombination of pre-existing CE knowledge is facilitated by the cognitive proximity of regions' knowledge bases with the CE technologies, on the other hand, it is the complementarity with the digital knowledge that makes the former prerequisite less important. Indeed, the cumulated competences in the digital field complementary to the circular one might enable regions to develop new knowledge as a result of the CE knowledge recombinations, making the generation process of new technological solutions more accessible to regions that have a knowledge base less cognitively close to the CE field. Then, digital

Table 4 – CE Recombinations, Localized Knowledge and Digital Complementarities

	-1	*-2*	*-3*
GT Stock	0.1900*** (0.0511)	0.1816*** (0.0483)	0.1675*** (0.0484)
DG Stock	0.0745* (0.0399)		
DG compl Stock		0.1365*** (0.0428)	0.3192*** (0.0777)
DG non-compl Stock		0.0428 (0.0406)	0.0013 (0.0436)
CE rel	29842*** (0.4896)	27995*** (0.4560)	33751*** (0.5044)
DG compl Stock * CE rel			-0.4858*** (0.1740)
GDPpc	0.1767** (0.0745)	0.2632*** (0.0806)	0.2560*** (0.0783)
Constant	-1.3600** (0.6415)	-1.9809*** (0.6755)	-1.8904*** (0.6529)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
Observations	1,345	1,345	1,345
R^2	0.9691	0.9697	0.9701
Adjusted R^2	0.9620	0.9627	0.9632
F Statistic	1.370.300***	1.393.549***	1.406.849***

Notes: Dep var: regional stock of patents citing CE-related technologies. Explanatory variables are log transformed and lagged by one year. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: Authors' elaboration

complementary knowledge not only contributes to the development of new technological knowledge in a direct way, but it also allows to overcome the risk of the lock-in path due to relatedness.

In light of the results presented so far, we expect that it is not the endowment of digital technologies per se that is conducive to CE recombination but rather its complementarity with CE technologies. To highlight the role of complementarity, we estimate models 2 and 3 by distinguishing between the stock of non-complementary digital technologies and the stock of the complementary ones. Results of these additional estimations are presented in Table 4. Column 1 reports our baseline specification, where the overall stock of digital technologies (both complementary and non-complementary) is included. We estimate a positive coefficient for the *DG stock* variable, though modest in magnitude and statistical significance. In line with our previous findings, the estimated coefficient of the digital complementary knowledge stock is still positive and statistically significant in columns 2 and 3 of Table 4. Interestingly, we find a non-significant role of the stock of non-complementary digital technologies on the regional ability to recombine circular knowledge, as indicated by the non-significant estimated coefficient of *DG non-compl Stock*. Lastly, the role of complementary digital technologies in attenuating the relatedness of CE knowledge is also confirmed.

5. Conclusions

Building on the geography of innovation literature, this chapter investigated the role of cumulated knowledge capabilities in a regional context on the recombination of localized knowledge in the increasingly relevant and promising field of the Circular Economy. Although governments and institutions worldwide are adopting and implementing CE practices in industrial and economic policies and strategies, aiming at shifting from a linear to a circular economic model, innovation and regional studies have posed little attention to the innovative dynamics leading to the generation and exploitation of CE related technologies. Specifically, systematic evidence on the mechanisms that facilitate the regional recombinant dynamics around circular technologies and lead to the development of new knowledge is still missing. By exploiting a sample of European NUTS-2 regions over the period 1980- 2015, our analysis aims at providing new evidence on the relationship between localized knowledge capabilities and the successful recombination of CE-related knowledge that leads to the generation of new knowledge. We show that the endowment of cumulated green knowledge and digital knowledge complementary to the circular one facilitates regional recombination processes of CE-related technologies. Our findings suggest that the know-how at the heart of the envisaged twin-transition, together with the importance of complementary digital capabilities, might enable regional recombination dynamics of circular knowledge, that can accelerate the achievement of a sustainable transition.

These results contribute to the existing literature in two major ways. First, opening the black box of the mechanisms behind the generation of new knowledge by means of the recombination of circular technology, we highlight the crucial role of local cumulated capabilities in European regions. We make a step forward in the understanding of regional recombinant dynamics and show that green-digital local capabilities are essential to trigger continuous knowledge improvements accelerating the path toward a sustainable transition. Further, we contribute the debate on the "twin-transition" in regional economies by showing that the enabling role of digital technologies in integrating multiple knowledge bits, dispersed in the technology space, is more effective when regions are endowed with digital technological capabilities that are complementary to the circular field.

This chapter also contributes the public debate in term of policy implications. Designing instruments to sustain regional innovative activities directing them toward green and digital technologies and reinforcing the existing local knowledge capabilities could be a leverage for the elaboration of strategies promoting research and innovation in the CE domain and the successful integration of circular knowledge in technological advancements. This implies the need to strengthen the institutional frameworks providing policy tools and incentives that facilitate the effective transfer of technological capabilities acquired in green and digital complementary fields, stimulating localized spillovers. Moreover, fostering the identification and generation of digital complementary technologies requires the design of strategic policies aimed at supporting the exploitation of knowledge hybridization, complementarities, and spillover between CE and digital capabilities. Lastly, policy efforts supporting the creation of positive network dynamics among regional actors might be crucial to sustain the development and integration of different and complementary skills and competences.

This study presents some limitations. First, we acknowledge that the classification of CE patents provided by the EC, being mainly focused on wastewater treatment or waste management, may only represent a subset of the potential technology advancements in the fields. At the same time, we rely on the efforts put forth by the European Commission in the CE monitoring framework in order to avoid subjectivity and facilitate comparison with other studies. A second limitation is related to the emphasis put on the codified side regarding the CE knowledge that may come at the cost of underestimating the broad introduction and adoption of CE practices. Nevertheless, given the increasing concerns about the need to understand innovation processes for a sustainable CE transition, recent contributions in the literature highlighted that while innovation activities in CE are still in the development phase, the wide potential of knowledge advancements and the recombination opportunities make the search for radical solutions for a successful CE transition increasingly reliant on technological efforts.

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Transizione Circolare e dinamiche ricombinatorie nelle regioni europee: il ruolo della conoscenza localizzata e della complementarietà tecnologica digitale

Sommario

Il raggiungimento di una transizione verde e sostenibile è una delle principali sfide che l'Europa sta affrontando. Tale transizione impone la necessità di muoversi sempre più verso un'Economia Circolare (CE). Questo richiede una maggiore comprensione della relazione tra innovazione, tecnologie e CE che ha ricevuto relativamente meno attenzione nella letteratura esistente, soprattutto a livello regionale. Questo capitolo si inserisce in questo dibattito e si pone l'obiettivo di esplorare le dinamiche di ricombinazione delle tecnologie CE a livello regionale, concentrandosi sul ruolo della conoscenza localizzata, delle capacità accumulate nel dominio tecnologico green e della complementarità con le tecnologie digitali. L'analisi empirica è condotta su dati raccolti per le regioni europee (NUTS2) tra il 1985-2015 e suggerisce che le capacità localizzate green e digitali complementari favoriscono la capacità delle regioni di assorbire e integrare nuove opportunità tecnologiche in ricombinazioni basate su tecnologie circolari, rappresentando quindi un importante stimolo verso una transizione sostenibile in ambito regionale.

CCIs and Regional Resilience in Transition Periods. Heterogeneity in Advanced and Lagging EU Regions

*Roberto Dellisanti**

Abstract

European regions are facing an unprecedented series of challenges deriving from a continuously changing world. The literature focuses on the uneven capacity of places to react to crises of different kinds, highlighting the different sources of regional resilience. Among these forces, creativity finds limited attention despite its capacity to trigger innovation and competitiveness for regions during transition periods. This chapter aims to discuss the capacity of Cultural and Creative Industries (CCIs) to trigger virtuous cycles for the recovery of the EU regions considering their different development stages, highlighting that different regions in transition benefit from different creative and cultural environments.

1. Introduction

In the last decade, especially after the 2008 financial crisis, we became used to large economic and social shocks (e.g. debt crisis, COVID19 pandemic, Russian invasion of Ukraine) deeply impacting our economies. The effects of these shocks were not only profound, but they resulted to be spatially uneven with territories showing heterogeneous resilience performances.

However, the continuously updated ways to discuss regional resilience is an indication of how complex is to deal with this concept. Generally, literature refers to it as the capacity of actors to cope with shocks and this allow to understand the heterogeneous local performances (Diodato, Weterings, 2015; Fingleton *et al*., 2012), with the aim of understanding their different responses (Capello, Caragliu, 2016; Capello *et al*., 2015).

In considering regional resilience in the context of the 2008 financial crisis, this chapter aims to focus on local creativity as a key resilience factor, an aspect that finds limited attention in the recent literature. In fact, besides the traditional growth drivers, the competitiveness of a local economy builds also on intangible,

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cognitive ones (Capello *et al.*, 2011) like culture and creativity (Capello *et al.*, 2020; Cerisola, 2019). Hence, it is possible to argue that the local cultural and creative setting influences its capacity to mitigate negative shocks (Bellandi, Santini, 2017). In this context, among the most relevant creative factors sparking off the resilience of regions, the role played by Cultural and Creative Industries (CCIs) deserves more attention, due to their capacity to feed local economies by products at the crossroad between culture and innovation.

Furthermore, the contribution of creative actors to the local resilience is expected to depend on the development stage of the region (Faggian *et al*. 2018; Giannakis, Bruggeman, 2020; Lagravinese, 2015). In fact, when a global crisis arises, lagging and more developed regions face it from a different starting point and this is expected to cause a different capacity to exploit CCIs and their creativity for resilience performances.

The interesting part of this story is to evaluate whether CCIs act as a convergence factor, reducing the gap between areas, or as a divergence one, heightening the economic gap. Therefore, the aim of this work is to discuss the implications of creativity on regional resilience and to test the multiplicative effects stemming from an advanced stage of local socio-economic development. More specifically, the contribution of CCIs will be evaluated comparing lagging and non-lagging regions, in the attempt to detect the conditions behind regional divergence or convergence.

Nonetheless, this ambitious aim sets some challenges to this work. First, the literature on the three aspects needs to be bridged, especially linking regional resilience with CCIs' creativity, discussing how their capacity of generating creativity may be translated either into a convergence factor for lagging behind regions or into a divergence factor for already developed ones.

Second, it calls for a deep discussion on CCIs and on the heterogeneity characterising these sectors. Being at the crossroad of crafts, arts, and technological innovations, they result to express creativity in very different ways. Moreover, this creativity shows also different levels of intensity according to where it flourishes, as the result of different cultural settings.

This work is structured as follows. First, it presents a review on the main aspects treated by this work, focusing on the literature approach to CCIs and their classification (section 2), and it considers the relationship between CCIs and regional economic resilience (section 3).

Second, thanks to an original database of CCIs across European NUTS3 regions, section 4 presents both a methodology to distinguish between *Inventive* vs. CCIs (4.1) and the approach to regional resilience for regions in transition (4.2).

Third, empirical results are presented in section 5, while section 6 concludes with discussions and policy implications.

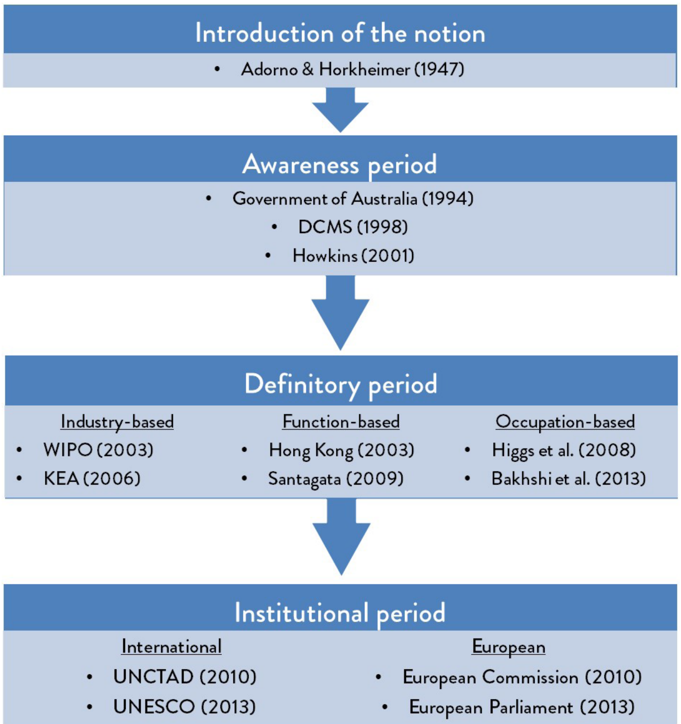
2. The Evolution of the Notion of CCIs and a Definition

In order to understand CCIs' role in shaping regional resilience, it is important to understand how literature considers this peculiar group of sector.

In the last 20 years, a huge amount of academic research put emphasis on the role of creativity at the industrial level, highlighting its intangible and pliable nature that make it difficult to map, also in CCIs. In the attempt of detecting creativity, CCIs have been defined and conceptualised in the course of the years. Figure 1 presents the evolution of the notions of CCIs, identifying four main conceptual approaches.

Until the mid of the 90s, CCIs found little space in scholarly and institutional works. In their 1947 *Dialektik der Aufklärung* (Dialectic of Enlightenment), Adorno and Horkheimer presented term 'culture industry' as a radical critique of mass entertainment. Since cultural activities became uniformly produced and made available for all, they defined activities like radio and music as a 'mass deception'.

Figure 1 – The Evolution of the Notions of CCIs



Source: Author's elaboration from Dellisanti (2022)

However, especially due to their fast growth, the story of CCIs changed in 1994 when the Australian Government published the Creative Nation. Cultural industries became a policy object to foster social and economic development, distancing them from the previous elitist dimension (Government of Australia, 1994).

In Europe, the recognition of CCIs as important aspect was due to the two notable Mapping Documents by the Department of Culture Media and Sport (DCMS) that determined the course of this literature in the coming years. Creative industries were defined as 'those industries which have their origin in individual creativity, skill and talent and which have a potential for wealth and job creation through the generation and exploitation of intellectual property' (DCMS, 1998, 2001).

In the same vein, John Howkins stressed on the change in the economic paradigm fostered by creative industries. Building on the 'exploitation of intellectual property rights' promoted some years before by the DCMS, Howkins linked intellectual property rights (IPRs) and creativity, and this choice was extremely relevant also for future researches.

Once the relevance of creativity in CCIs was widely acknowledged by scholars, literature put the accent on the fact that, although all based on creativity, CCIs are heterogeneous. This heterogeneity was described in very different ways: in some cases stressing the differences *across* industries (KEA, 2006; WIPO, 2003), for example comparing the creative and cultural bases and outputs of music and advertising industries; in others, instead, retracing the heterogeneity in the complexity of the different production processes *within* single industries (Santagata, 2009; University of Hong Kong, 2003).

Moreover, in the attempt of understanding the creative element in CCIs, a relevant stream of research proposed to integrate the occupational approach to the industrial one, linking the creative tasks and skills present in an industry to determine the *creative intensity* (Bakhshi *et al*., 2013; Higgs *et al*., 2008).

In addition to these studies, international institutions contributed to the debate adding a normative perspective. The UNCTAD Creative Economy Report enlarged substantially the scope of CCIs considering 'any economic activity producing symbolic products with a heavy reliance on intellectual property and for as wide a market as possible' (UNCTAD, 2010). It contributed to link creativity to innovation, reinforcing the bound with IPRs as output of CCIs. The point of view presented by the UNESCO in 2013, instead, recognises that CCIs also have a social positive effect. They not merely stimulate economic growth, but they also improve life conditions, enhancing local image and prestige (UNESCO, 2013).

Finally, building on the *Green Paper* (EC, 2010) and on the *Creative Europe* programme (European Parliament, 2013), the European institutions aim to harness the power of culture and creativity to promote awareness of European strong identity and to support a key industrial segment for EU economy.

The effort made for retracing the evolution of the approaches to CCIs made possible to understand that the intensities and the forms of creativity within CCIs drive their heterogeneity. However, the conceptualization of the heterogeneity requires additional effort in order to better identify CCIs and their creativity. This will be the subject of the next section.

The intrinsic heterogeneity within CCIs represent, thus, a challenge for all studies focusing on them. In fact, although CCIs are formed by sectors that rely on culture and individual creativity, culture and creativity translate in CCIs in very different ways and it is natural to imagine that both cultural values and creative expressions generated are not alike.

A widely shared definition of CCIs is still missing, even if scholars proposed alternative conceptual methods for their classification. In this work, following Dellisanti (2022), defining creativity in CCIs requires three key perspectives: a) creativity is embedded in the output of the production process; b) creativity is a multifaceted concept and the output can take different forms; c) creativity is expressed at different levels of intensity according to the place.

Therefore, creativity can be measured through indicators of innovation, from the classical patent-based approach to the inclusion of *softer* forms of innovation, capturing the different essences of creativity (Stoneman, 2010).[1] Moreover, being territories the loci of collective learning processes (Camagni, 1991) and of identity and sense of belonging (Panzera, 2022), they feed local creativity shaping its intensity.

From all that precedes, in order to identify and define CCIs across regions, these two considerations are applied to a well-established list of industries belonging to the *Macrosector* of CCI, as in the *White Paper on Creativity* by Walter Santagata in 2009. Santagata's definition is applied because it acknowledges that creativity may express differently in different sectors, and the list is extremely accurate presenting a precise sectorial disaggregation.

To Santagata's list of CCIs, creative (*Inventive*) sectors are separated out from non-creative ones (*Replicative*), according to the intensity of creativity generation and considering that the forms of creativity are heterogeneous. The empirical methodology in this respect is presented in section 3.

Moreover, the distinction between *Inventive* and *Replicative* CCIs is made at the regional level, accounting for different degree of creativity in each territory.

1. Paul Stoneman's *Soft Innovation – Economics, Product Aesthetics, and the Creative Industries* provided a critical view of the *Oslo Manual* (OECD, Eurostat, 2005) that defined innovation as 'the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations'. In Stoneman's idea, there exist other forms of innovation that are not included in the OECD definition. Indeed, in the new "weightless economy" it is illogical to exclude activities like films or music from innovative activities, typical CCIs.

In this way, the employment in creative CCIs for each NUTS3 in Europe can be built. A so fine distinction of CCIs, based on their creative intensity, will be useful for assessing the role of these actors in shaping regional responses to shocks. In fact, being creativity a key asset for regional economic competitiveness, its forms and its intensity may help regions to be resilient during transition periods. The potential role of CCIs for lagging and transition regions is conceptually discussed in the next section.

3. CCIs in Lagging Regions: Challenges or Opportunities for Resilience?

3.1. Regional Resilience in Brief

In the last decade, especially after the economic crises (2007-2008, 2012-2013) that European economies faced, scholars and institutions aimed to find the determinants of regional growth (Treb, Donaldson, 2021; Cicerone *et al*., 2020)examining the extent to which network connectedness and centrality of a province's exports is related to its economic performance. We construct a new Product Space Position (PSP. However, latest empirical investigations highlight the presence of a lot of unexplained growth from classical models (Grillitsch *et al*. 2021). One of the possible explanations is the drastic change of the regional growth patterns after the crisis with heterogeneous impacts on different territories (Dijkstra *et al*., 2015).

Building on this discussion, the concept of regional economic resilience was introduced as a complement to growth theories, offering a different perspective to understand the capacity of places to react to shocks. At the basis of this concept, there is the acknowledgement that regional economies unevenly respond to shocks (Gardiner *et al*., 2013; Martin *et al*., 2016) as a crisis may drastically change them and their behaviour.

The concept of resilience is a complement to growth because a region can be resilient even without growth, only limiting the negative effects of a shock. However, the local growth trajectories are extremely uneven and the reasons behind this process are not yet clear. Despite the large interest on the concept of economic resilience, literature described the phenomenon mostly through three approaches: the engineering, the ecological, and the evolutionary/adaptive ones (Martin, 2012; Modica, Reggiani, 2015). The first considers resilience as the ability of a system to return to, or resume, its stable equilibrium after a shock or disturbance. The second relates resilience to the scale of a shock or disturbance that a system can absorb before it moves to a new stable state. Finally, the last interprets resilience as the ability of a system to undergo adapt to the shock, so to minimize the negative impact of a shock.

Nonetheless, the choice of the most appropriate approach to resilience is not the only issue to be treated cautiously. It is also relevant to understand the forms that resilience can take and how to measure them. Martin (2012) translates regional resilience into four dimensions: resistance, recovery, re-orientation, and renewal.

The first two dimensions outline two different static situations: *resistance* considers what happens during a crisis, so to assess how able a region was in softening the negative impacts; *recovery*, instead, interprets what happens after the crisis, considering the regional performance in lifting the head up again. Instead, the last two embed the concept of *adaptability*. Re-orienting and renewing the growth path requires that places dynamically adapt to different conditions. In this sense, adaptive resilience may be seen as a combination of recovery and resistance.

3.2. Different Approaches to Lagging Regions

The discussion on regional economic resilience is particularly relevant in the context of lagging regions due to their disadvantaged starting point. In fact, economic crises may worsen the economic disparities across places and create the conditions for a wider divergence in the development patterns.

Conceptually, a lagging region can be defined as a region whose development stage is below a given threshold, relative to a reference area. The level of development is generally associated to observable characteristics, such as level of wealth or growth performance.

In most of the cases, the concept of lagging region is used to target policies aimed at reducing the disparities within a given reference area. In the case of the EU, cohesion policy covers every region (i.e. all regions are eligible) but structural funds are mostly targeted where they are most needed. More specifically, the European Commission defines three groups of regions (EC, 2014):

- Less developed: where GDP per capita is under 75% of the EU average;
- Transition: where GDP per capita is between 75% and 90% of the EU average;
- More developed: where GDP per capita is above 90% of the EU average.

However, in its 6th Cohesion Report, the European Commission itself considers that lagging regions may be identified at the intersection of two categories: the lower-than-average capacity to grow, and the lower-than-average income level. This distinction has the merit to have acknowledged for the first time that the concept of lag is heterogeneous. In fact, comparing Eastern and Southern European regions, they showed different trajectories. The former, despite remaining very poor, had grown well above the European average (low-income regions); the latter, instead, although starting from a higher level of development, had failed to converge (low-growth regions).

Considering the concept of resilience in the context of lagging regions opens interesting questions for economic research. In fact, together with the classical conditions that are considered relevant in shaping regional economic resilience, such as the economic regional structure and the sectoral composition (Brown, Greenbaum, 2017; Di Caro, 2017; Crescenzi *et al*., 2016; van Oort *et al*., 2015), further discussion is needed to evaluate the role of intangible regional assets such as creativity in shaping regional resilience, especially in lagging areas.

3.3. Creativity as a Regional Relaunch Factor

A region's capacity to face shocks can be linked with its history and legacy, embodied in the industrial, network and institutional structures (Boschma, 2015). Due to its intangibility, creativity represents one of the dimensions to understand how regions react during and after a turmoil. Historical and cultural heritage together with creativity and traditions are key aspects to understand the foundations behind new pathways of regional development (Panzera, 2022). Cultural backgrounds and institutions, in fact, influence deeply people's creativity (Serafinelli, Tabellini, 2022) and, in turn, creativity triggers regional adaptability through its territorial, cultural, and social capital (Antonietti, Boschma, 2021; Fratesi, Perucca, 2018).

In this direction, literature highlighted that creativity represents a key element to trigger growth in lagging areas (Stephens *et al*., 2013), although a deeper reflection on the heterogeneity of creativity and its knowledge bases may be relevant. Thus, a more comprehensive picture of an intangible asset for regional economies such creativity could help to refine the interpretation of its growth-enhancing capacity (Barzotto *et al*., 2019; Faggian *et al*., 2017).

Due to their strong cultural essence and their capacity to generate creative ideas, CCIs represent pivotal actors for regional economies. They not only embed the cultural and creative heritage of the place (Santagata, 2009), but they are considered among the most innovative actors for an economy (Deloitte 2021; Hartley *et al*. 2013; Müller *et al*., 2009).

However, CCIs' role in driving the economic response to shocks finds limited attention in the literature, especially when considering the propulsive role creativity can exert for lagging regions. In this respect, although shocks changed the geographical distribution of CCIs in space (Cruz-Santos, Teixeira, 2021), they demonstrated to work as a resilience factor for areas to face economic and natural shocks, like in the case of 2016-2017 Central Italy earthquake (Cerquetti, Cutrini, 2021) or in the case of Sofia, Bulgaria through a re-invention of the economic system (Dainov, 2009).

Nonetheless, literature overlooks CCIs' ability to sustain the economic system thanks to new ideas, processes, and products. From this perspective, CCIs could explain part of the regional ability to adapt its structure in response to shocks thanks to the introduction of innovative products and sustaining the local competitiveness.

Bridging creativity and resilience, the question that this chapter aims to reply to is, therefore, whether creativity in CCIs may represent a relevant resilience factor for lagging regions in escaping from a growth trap. In other words, do CCIs play as propulsive actors to help lagging regions respond and recover from shocks? Is the creative/inventive component in CCIs capable of reinforcing this mechanism?

In order to reply to these questions, an original database of CCIs at the regional level is needed, capable to refine the classification of CCIs based on their capacity to *create*. Moreover, it is also required a rigorous empirical methodology to link CCIs and economic resilience, distinguishing between different typologies of regions in transition. Therefore, data and methods to measure the CCIs-resilience nexus are presented in the next section.

4. CCIs-resilience Nexus: Data and Methodology

4.1. Measuring Inventive and Replicative CCIs: a regional-industrial approach

In order to assess CCIs' contribution to regional economic resilience, it is necessary to set the scene of the data and methodology employed. To classify CCIs in the way presented in Section 2, the approach presented in Dellisanti (2022) is used.

Each sector $i \in CCIs$ should be classified according to the intensity of producing creativity, considering different possible creative expressions. In order to capture all forms of creativity, we use the intensity of intellectual property rights, considering patents for technological creativity, trademarks for *symbolic* creativity, and copyrights for *artistic* one.

As far as technological and symbolic creativity are concerned, the creative intensity of a sector in a region (i.e. the number of either trademarks or patents, per employee) is computed as a relative measure with respect to the EU level, as follows:

$$i \in CCIs \rightarrow \begin{cases} not\ IP-intense,\ if\ \dfrac{PR_{i,r}}{E_{i,r}} \leq \dfrac{PR_{i,EU}}{E_{i,EU}} \\ IP-intense,\ otherwise \end{cases} \qquad [1]$$

where *PR* stands for Property Rights (i.e. patent or trademark), *E* refers to employees, *r* and *i* are respectively the general region and the general sector.

Concerning artistic creativity, instead, a so high level of granularity in the copyright data is not available, since copyrights are not firm-specific.[2] To cope with this issue, the list of copyright-intense sectors provided by EPO and EUIPO (2016) is used.

The employment in *Inventive* CCIs for each region is therefore built as the sum of employment in copyright-intense sectors and of those sectors that register a creativity intensity (patent or a trademark) higher than the EU mean. Similarly, regional employment in *Replicative* CCIs is composed by the sum of employment of those sectors that register a lower creative intensity than the EU average and of those not part of the copyright-intense sectors.

In terms of geographical scope, this analysis covers all NUTS3 regions of the EU (UK included)[3] and Orbis data was used to capture both the level of employment and IPRs (patents and trademarks) at fine industrial and geographical scale.[4] Matching Orbis information with total regional employment level (source ARDECO),[5] the share of regional employment in *Inventive* and *Replicative* CCIs was computed.

4.2. Model Specification

The contribution of CCIs to the resilience of regions is estimated through a multinomial logit model, as in (2).

$$RGP_{r,t} = X_{r,t_0}\beta + \gamma\left(CCIs_{r,t_0} * lagging_r\right) + \varepsilon_{r,t} \qquad [2]$$

The dependent variable (Regional Growth Pattern, henceforth RGP) of this specification is a categorical variable capturing the resilience category which a region belongs to. In line with a previous study, (Capello, Dellisanti, *forthcoming*), the categorical variable is obtained comparing the regional GDP growth at NUTS3 level with respect to the EU median in two periods, the crisis (2008-2012) and the post-crisis (2013-2017).[6] This gives rise to four possible patterns (Capello, Dellisanti, *forthcoming*):

- *Crisis* regions, i.e. those that performed relatively worse than the EU median in both periods. These regions did not manage to both resist to and recover from the shock;

2. The ownership of works of art, literature, music, multimedia and other protectable works in general resides in their creators (cfr. EUIPO website).
3. Data for Northern Ireland is not available due to inconsistencies found in Orbis.
4. Orbis contains information on the amount of IPRs produced at the establishment level that can be grouped at the region-industry level.
5. ARDECO is the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy, maintained and updated by the Joint Research Centre.
6. Notice that the performances in the two periods are independent one another, the only reference is the median growth within each period.

- *Resistance* regions: i.e. those that registered a higher than EU median growth during the crisis period and a lower than EU median growth after it;
- *Recovery* regions: i.e. those that, on the contrary, were capable of growing more than EU median the after the crisis, although they displayed a lower than EU median growth during it;
- *Adaptive resilience* regions: i.e. those that performed higher than EU median values in both periods. These regions were capable of containing the negative effects of the crisis and, after it, maintaining the divergence performance compared to the median cases.

The explanatory variable of interest is represented by the share of employment in *Inventive* and *Replicative* CCIs in each region, interacted with a dummy variable capturing whether a region is in a lagging development stage. The regional development stage is derived from the subdivision of regions by eligibility category for structural funds (EC, 2014). For the sake of this work, lagging (or transition) regions were identified as those regions falling into either less developed or transition categories.

Finally, a set of control variables X_r is included, based on the vast literature on resilience. This set accounts for: a) the initial level of GDP per capita, to capture the convergence effect of poorer areas; b) market potential, to account for the economic size;[7] c) the manufacturing employment share to proxy the regional industrial structure;[8] d) the quality of human capital, proxied by the education level; e) patents *per capita* to measure regional innovative capacity; f) multimodal accessibility, usually considered a success factor;[9] g) regional EU funds expenditure per capita, spent to reinforce regional economies;[10] h) economic diversity index, to consider that diverse industry bases made regions faring better during crises (Brown, Greenbaum, 2017); i) settlement structure (metro vs non-metro area), proved to be a relevant factor in explaining the regional performance (Capello *et al*., 2015; Dijkstra *et al*., 2015); and j) the attraction of migrants, capable to mitigate the effects of crises in periods of population

7. Market potential is the sum of internal and external market potential (IMP and EMP, respectively), proxied by the Value Added (VA) generated internally and in the neighbouring regions (Breinlich, 2006; Harris, 1954). $IMP_r + EMP_r = VA_r + \sum_{s \neq r} w_{r,s} * VA_s$ where $w_{r,s}$ is the generic element of the inverse geographical distances matrix.

8. Services and manufacturing employment shares are strongly correlated and the inclusion of both could cause multicollinearity. Only the latter is considered.

9. The most used indicator of accessibility is the potential multimodal accessibility index provided by ESPON (ESPON, 2015). Due to data limitation, the measure of accessibility refers to 2006 and not to 2008.

10. Both European Regional Development Fund (ERDF) and European Social Fund (ESF) funds are considered in this work.

stagnation (ESPON, 2008; Giannakis, Bruggeman, 2017). Descriptive statistics of all variables are presented in Table 1.[11]

5. CCIs and Resilience for Regions in Transition

The results of the multinomial logit (equation (2) are presented in Table 2. Columns (1)-(3) consider *Replicative* CCIs as main regressor; columns (4)-(6) consider *Inventive* ones. Looking at the coefficients, *Inventive* and *Replicative* activities seem to act differently, especially for what concerns the contribution to adaptive resilience and considering different regions in transition.

More in detail, positive and significant coefficients are associated to the contribution of both forms of CCIs in triggering the recovery of lagging regions. This supports the idea that CCIs contribute to reinforcing the response of places after crises. Lagging places benefit from a stronger presence of CCIs, fuelling the economic system and stimulating a cultural and creative demand that is reflected in the speed of recovery.

Moreover, a positive and significant effect is associated to only *Inventive* CCIs in developed areas, triggering their adaptive resilience. This is a strong and interesting result as it mirrors the capacity of CCIs to spark off a wider economic development. In fact, the adaptive resilience captures the positive and virtuous regional performance both during and after the crisis.

However, this effect may also generate territorial inequalities because it concerns the growth of already advanced areas at the expenses of lagging places.

All these considerations derived from the regression output need to be validated considering marginal effects. In fact, multinomial logit models present coefficients whose magnitude and significance shall be considered *relative to* the reference group. In this work, the *Crisis* category represents the reference. Therefore, Average Marginal Effects (AMEs) were calculated in order to check the significance of the coefficients within each group.
Figure 2 presents marginal effects of CCIs for *Recovery* and *Adaptive resilience* patterns, considering lagging and non-lagging regions, while those associated to *Crisis* and *Resistance* are not shown due to their poor significance levels.

Considering *Recovery*, the marginal effects confirm the findings of the regression output and the interpretation: both *Inventive* and *Replicative* CCIs support regional *recovery* but only in lagging regions.

Considering *Adaptive resilience*, instead, thanks to the process of new knowledge generation, only *Inventive* CCIs set the conditions for the regional resilience after an economic shock such as the financial crisis 2008-2012 but only in non-lagging areas.

11. Dependent variables are measured in 2008, i.e. the beginning of period 1, in order to limit any simultaneity bias.

Table 1 – Descriptive Statistics of the Variables Included in the Regression

Variable description	*n.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Data source*
Employment share in Inventive CCIs	1,332	0.012	0.018	0	0.201	Orbis & Ardeco database
Employment share in Replicative CCIs	1,332	0.016	0.025	0	0.326	Orbis & Ardeco database
Lagging region (dummy)	1,332	0.399	0.490	0	1	EC (2014)
Logarithm of GDP per capita	1,332	9.988	0.436	8.678	12.776	Ardeco
Manufacturing empl. share	1,332	0.263	0.089	0.042	0.552	Ardeco
Share of tertiary educated individuals	1,332	15.833	8.908	0	47	ESPON
European funds expenditure per capita	1,332	0.555	1.236	0.004	28.960	Cohesion Data
Logarithm of GVA	1,332	22.248	1.062	18.956	25.834	Ardeco
Logarithm of spatial lags of GVA	1,332	11.304	0.207	10.863	12.173	Ardeco
Innovativeness	1,332	0.538	1.341	0	24.562	OECD RegPat
Accessibility	1,332	92.922	39.035	4.280	299.979	ESPON
Economic diversity	1,332	4.253	0.453	2.166	5.424	Ardeco
Net migrations	1,332	11.823	42.074	-154.580	711.865	Eurostat
Metropolitan region	1,332	0.475	0.641	0	2	Eurostat

Source: Author's elaborations

Therefore, these results tell two different stories. First, all CCIs represent a convergence factor for lagging regional economies. A strong local presence of these actors helps places to reverse the negative effects suffered during the crisis and start a novel development path. The recovery after the crisis may then be followed by a reduction of the gap with developed areas.

Second, *Inventive* CCIs represent a divergence factor for developed regional economies. A strong local presence of highly innovative CCIs supports the adaptive resilience of places, through their capacity of creativity generation sustaining the economy to overperform both during and after the crisis. It can be considered a divergence factor because this effect applies only to already developed areas.

These results could be relevant for a deeper discussion on the contribution of CCIs to local economic growth and regional resilience. The creative economy

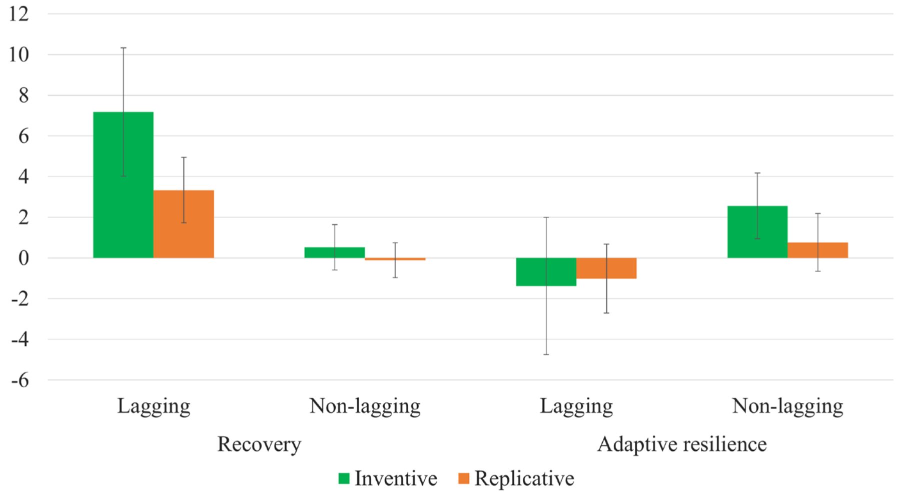
Table 2 – Regression Results of the Multinomial Logit Model on Resilience

	Replicative CCIs			*Inventive CCIs*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Variables	*Resistance*	*Recovery*	*Adaptive Resilience*	*Resistance*	*Recovery*	*Adaptive Resilience*
Empl. Replicative CCIs (%)	-4.5595 (6.050)	-1.0456 (4.061)	2.5318 (4.867)			
Empl. Replicative CCIs (%) * lagging	-1.7472 (7.987)	21.4311*** (6.988)	0.3577 (7.221)			
Empl. Inventive CCIs (%)				-3.8964 (7.513)	9.1044 (5.678)	16.6512 *** (6.354)
Empl. Inventive CCIs (%) * lagging				-6.2092 (14.754)	44.6501*** (12.931)	5.7690 (14.539)
GDP per capita (ln)	-0.6042* (0.314)	-0.6682** (0.302)	-0.8306*** (0.321)	-0.5764* (0.307)	-0.3316 (0.300)	-0.7011* (0.364)
Manufacturing empl. (%)	-2.1663 (1.360)	4.7129*** (1.232)	3.9076*** (1.221)	-2.2266 (1.366)	4.3265*** (1.328)	4.1074*** (1.254)
Share of tertiary educated individuals	0.1051*** (0.013)	0.0454*** (0.014)	0.1185*** (0.013)	0.1042*** (0.013)	0.0515*** (0.014)	0.1210*** (0.014)
European funds expenditure per capita	-0.4343*** (0.125)	-0.6052*** (0.146)	-0.6915*** (0.138)	-0.4528*** (0.127)	-0.5326*** (0.135)	-0.7334*** (0.144)
GVA (ln)	-0.2807** (0.143)	-0.3209** (0.150)	-0.2937** (0.144)	-0.2994** (0.142)	-0.2086 (0.149)	-0.2718* (0.142)
Spatial lags of GVA (ln)	-0.9297 (0.566)	-0.3688 (0.540)	-3.8290*** (0.586)	-0.9542* (0.553)	-0.0694 (0.533)	-3.5286*** (0.614)
Innovativeness	0.1557 (0.144)	0.2361 (0.147)	0.3402** (0.138)	0.1429 (0.138)	0.1873 (0.143)	0.3332** (0.137)
Accessibility	0.0025 (0.003)	0.0002 (0.003)	0.0042 (0.003)	0.0023 (0.003)	0.0007 (0.003)	0.0030 (0.004)
Economic diversity	0.4830** (0.214)	-0.3632 (0.224)	0.0679 (0.220)	0.4864** (0.213)	-0.2474 (0.231)	0.0511 (0.221)
Net migrations	0.0035 (0.003)	0.0071*** (0.002)	0.0020 (0.003)	0.0035 (0.003)	0.0080*** (0.002)	0.0033 (0.003)
Metropolitan region	0.0319 (0.166)	0.4848*** (0.167)	0.7426*** (0.162)	0.0364 (0.167)	0.4564*** (0.168)	0.7572*** (0.164)
Constant	19.3220*** (6.092)	16.9753*** (6.009)	54.1494*** (6.410)	19.7777*** (5.885)	7.2122 (5.829)	49.2290*** (7.184)
Observations	1,332	1,332	1,332	1,332	1,332	1,332
Model	Multinomial Logit	Multinomial Logit	Multinomial Logit	Multinomial Logit	Multinomial Logit	Multinomial Logit
Pseudo R2	0.154	0.154	0.154	0.154	0.154	0.154

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Reference category: Growth pattern=Crisis

Source: Author's elaborations

Figure 2 – Marginal effects of CCIs for Recovery and Ad. resilience patterns, considering lagging and non-lagging regions (95% CI shown)



Source: Author's elaborations

(here proxied by the presence of CCIs) proves to trigger the resilience of regions adapting to different situations. However, CCIs stimulate a virtuous circle at the regional level heterogeneously, according to both the level of development of the region and the inventive capacity of CCIs.

6. Conclusions

The turbulences that ran over our economies have strongly changed the way in which they function and the conditions behind their success. Many European regions found themselves trapped in a stagnating condition, such that some scholars are talking about a *Regional Development Trap* (Diemer *et al*., 2022), calling for additional studies on the conditions that may sustain local areas to escape from this trap.

Among the success factors for regional economies, wide convergence exists on the role played by creativity in general and by CCIs in particular. Creative activities, in fact, sustain the regional growth through the generation of products that are not only highly demanded (e.g. mass consumption goods, like books and clothes), but also highly *creative* in their essence (e.g. technological or artistic innovations).

This chapter provided with a novel perspective on the resilience of regions, offering some insights on the contribution of CCIs to sustaining local growth through creativity. More specifically, the results gave some interesting results also considering that the effect is heterogeneous according to the development stage of the area. On the one hand, lagging regions benefit from the mere presence of CCIs for the speeding up of the recovery after the crisis. On the other hand, the presence of specific *Inventive* CCIs sustain the adaptive resilience of non-lagging areas through their capacity to generate new ideas, products, and activities with a large creative component. Thanks to new knowledge, CCIs help already developed areas to transform and adapt to the structural changes triggered by the crisis.

In order to reach these results, the work put large effort on the methodological side. A more precise identification of CCIs and of their creative capacity allowed to distinguish between *Inventive* and *Replicative* activities, helping to disentangle their propulsive role. Moreover, the empirical approach to economic resilience allowed to capture in a single way the different forms of responses of a region to a shock. *Resistance*, *Recovery*, and *Adaptive Resilience* categories captured this heterogeneity and allowed to discuss resilience from different angles.

The main lesson that can be drawn from this analysis refers to the capacity of CCIs to drive the economic resilience of territories and this effect is not uniform across regions. The development stage of the region (lagging vs non-lagging) plays a role in understanding the phenomenon, also changing the marginal impact of CCIs in sustaining resilience. Therefore, CCIs may help different regions in transition to overcome a period of crisis.

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Industrie Culturali e Creative e resilienza regionale durante periodi di transizione. Eterogeneità fra regioni avanzate e in ritardo di sviluppo

Sommario

Le regioni europee si trovano ad affrontare una serie senza precedenti di sfide derivanti da un mondo in continua evoluzione. Nel cercare di spiegare gli impatti di questi macrotrend a livello regionale, la letteratura si è soffermata sulla capacità dei luoghi di reagire a crisi di diversa natura, evidenziando le diverse fonti di resilienza regionale. Tra queste, la creatività trova un'attenzione ancora limitata nonostante la sua capacità di innescare innovazione e competitività per le regioni durante i periodi di transizione. Questo capitolo si propone di discutere il ruolo delle industrie culturali e creative (ICC) nell'innescare cicli virtuosi per la ripresa delle regioni europee considerando le loro diverse fasi di sviluppo, evidenziando che diverse regioni in transizione beneficiano di diversi ambienti creativi e culturali.

Vulnerability to Poverty of the Tuscan Households During the Covid-19 Pandemic Outbreak

Laura Neri, Nicola Sciclone°*

Abstract

The importance of studying the changing nature of poverty and the monitoring of poverty conditions caused by the COVID pandemic have been stressed by the World Bank and other international institution. In this work, an effort is made to estimate non-monetary poverty measures at two different sub-regional levels in Tuscany thanks to an original data source obtained from the ad-hoc Survey on Vulnerability and Poverty planned and conducted in September 2021 by the Regional Institute for Economic Planning of Tuscany (IRPET) in collaboration with the University of Siena. The sample survey was carried out after the COVID-19 pandemic, and some of the items collected focused on the subjective perception of poverty eighteen months after the start of the pandemic. Moreover, we collected a battery of deprivation/vulnerability indicators referred on households' current situation (September 2021) and referred to the pre-pandemic period 2019 to allow a comparison between the two periods. In the empirical analysis, we estimate the percentage of households living in poverty conditions, at two different sub-regional levels, according to the traditional approach and three supplementary fuzzy measures of poverty, according to a multidimensional and fuzzy approach. We assess the quality of these estimates, assessing that for some small areas the accuracy was not sufficient, therefore we resorted to small area estimation methods.

1. Introduction

Policies for fighting poverty and social exclusion are among the tools identified for achieving the UN Sustainable Development Goal #1, "End poverty in all its forms and dimensions" (United Nations, 2015). Specifically, the 1.2 target states that by 2030 the share of individuals living in poverty should be at least halved.

The COVID-19 pandemic outbreak affects all segments of the population and is particularly detrimental to members of social groups in the most vulnerable

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situations. In the first year of the economic crisis associated with the Covid-19 pandemic, the World Bank stressed the importance of studying the changing nature of poverty and, therefore, the need to identify and profile the new poor (Mahler *et al*., 2022). The pandemic has created both a public health crisis and a severe crisis on both the global and national economies and continues to affect populations especially in the social-economic sphere. Some recent studies have shown that not all the EU felt the pandemic impact on their economies to the same extent: the southern European countries like Spain, Croatia, Greece, and Italy, where the tourism sector plays a relevant role, are the most fragile.

At the national level, the issue of the elimination of social, economic, and local inequalities is mentioned in the Inclusion and Cohesion mission of the National Recovery and Resilience Plan (NRRP) to support vulnerable people. The traditional literature on poverty analysis uses just the monetary metric and establishes a poverty threshold that produces a binary classification into poor and non-poor (Ravallion, 2016; Atkinson, 2019). Poverty estimates are computed at the national level (NUTS 0 with reference to the Nomenclature of Territorial Units for Statistics) and, only in some cases, at the regional level (NUTS 2) (Istat, 2022; Eurostat, 2020; Lemmi *et al*. 2019). Measures of multidimensional poverty, going beyond the exclusive use of monetary variables, have been developed in different contexts, mainly drawing on Sen's capability approach (Sen, 1993). Two prominent examples are represented by the "people at risk-of-poverty or social exclusion" indicator, by Eurostat, and the Multidimensional Poverty Index (MPI), by the Oxford Poverty and Human Development Initiative – OPHI (Alkire *et al*. 2015). The implementation of a multidimensional approach to poverty, as well as to deprivation or vulnerability needs up-to-date reliable data, the identification of the relevant dimensions, and the choice of how to summarise information to produce the final indicator. Evaluating the effect of a general economic crisis on living conditions, from a multidimensional perspective, is essential because the crisis can determine not only a reduction in available monetary resources, but can have repercussions in terms of, participation in social life, health conditions, food consumption behaviour, and healthy eating habits. In this framework, the several editions of the Special Survey of Italian Households launched by the Bank of Italy in the years 2020 and 2021 have provided timely information on household economic situation during the pandemic crisis, at the NUTS 1 level (Italian regions).

Due to the economic crisis, still ongoing, poverty area is expanding: individuals who were previously not poor go into poverty or/and who, in the absence of the crisis, would escape poverty, remain in poverty. There is the need to address poverty analysis at a domain level to understand whether and to what extent the processes of impoverishment have spread and in which territories and/or groups of the population the inequalities have changed. Indeed, the interaction between these local factors and such events as pandemics, wars and other shocks may generate a differentiated effect on a sub-regional scale, which must be investigated on the basis of data collected on the same scale, in a multidimensional perspective. This step is crucial to propose intervention strategies that account for the territorial heterogeneity and the specific needs of different groups of individuals and/or families. For these reasons, it becomes very important to concentrate the analysis on specific domains, such as provinces (NUTS 3) or other territorial levels or peculiar groups of the population, commonly labelled as "small area". In order to produce small area level accurate estimation, even in case of very limited sample size, we adopt small area estimation methods (Pratesi, 2016; Betti, Lemmi, 2014).

In this paper, the main aim is to study the impact of COVID-19 pandemics on economic poverty and deprivation/vulnerability, in a specific Italian region and even at sub-regional level. The focus is on Tuscany, a region that heavily relies on exports and various forms of tourism. Moreover, considering the heterogeneity of the regional territory, we retain that it is particularly interesting to analyse the phenomenon of economic poverty and vulnerability considering a sub-regional level, like NUTS 3 level or specific significant areas, officially defined by IRPET according to economic and geographical criteria, and to examine the association between COVID-19 economic crisis and the previous status of area deprivation.

Section 2 introduces the concept of deprivation and vulnerability according to the meaning of the paper; then the survey and the statistical methods adopted, with preliminary insight on the data; Section 3 describes the empirical analysis and the results obtained at different level of disaggregation; Section 4 concludes the paper with further remarks.

2. Deprivation and Vulnerability: Definition, Data and Methods

2.1. Definition

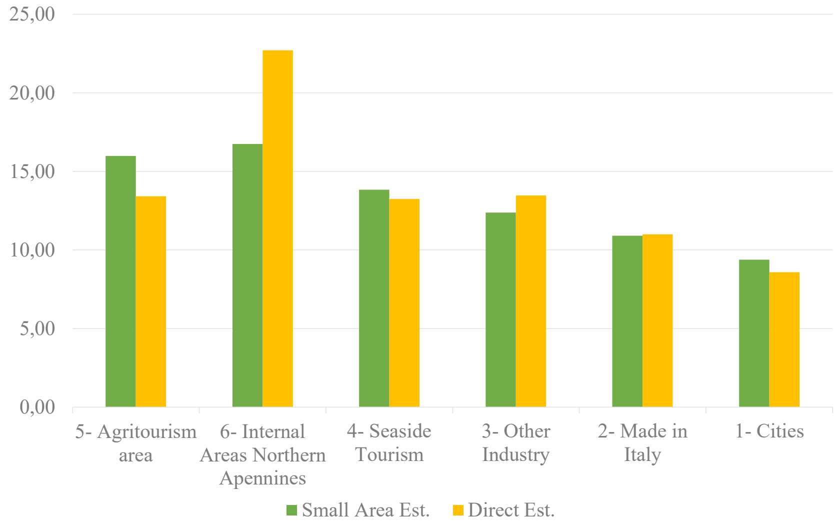
Deprivation and vulnerability can result from various factors such as physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards.

In the context of the COVID-19 crisis, surely people experiencing an economic crisis, but also multiple deprivations. In our work, we consider households as deprived and/or vulnerable by assessing whether they could cover their usual and unexpected expenditures, such as: affording adequate food and utilities, cope costs for transport, education, health, leisure, and to cope with unexpected expenses. These concepts may be more widespread than monetary poverty. In the paper, we adopt a multidimensional and fuzzy approach to overcome the limitation due to considering just a monetary variable to compute standard poverty measures; moreover we overcome the limitation of considering poverty as a binary phenomenon (poor/non-poor), adopting the fuzzy approach. Considering the aim of producing estimates for small domains in Tuscany, we gain of another important advantage: fuzzy measures are more informative than traditional economic poverty measures and have smaller standard errors (Betti *et al*., 2018). Therefore, fuzzy measures are more useful for subnational measures (Betti *et al*., 2012), which means that we can obtain estimations for areas with relatively small samples that are more statistically significant than those yielded by other measurement approaches.

2.2. Data

To achieve our research aims, we refer to the sample survey "Indagine sulla Vulnerabilità alla Povertà" planned and conducted in September 2021 by the Regional Institute for Economic Planning of Tuscany (IRPET). The survey was designed to analyse on the economic and social features of the Tuscan households, with particular attention to the current economic situation and prospects. A sample size of 2512 households was achieved planning the sample design to achieve a representative sample at NUTS 3 level (Province's level). Interviews was conducted by Computer Assisted Telephone Interview (C.A.T.I) and Computer Assisted Mobile Interview (C.A.M.I) methods, interviewing one adult household's member. After a weighting procedure, the sample totals conform to the population totals as regard to gender and age groups. As regards to item nonresponse, missing data have been imputed by deductive imputations based on logical or mathematical relationships between the variables, where it was possible. As regards to the remaining missing values we decided to delete the thirteen units having missing values for all the eleven key indicators collected for the current situation (2021) and for the pre-Covid normal situation, referred to 2019, that we consider as the core variables of the analysis. Accordingly, the valid units for the analysis were of 2499 households. Item nonresponse relative to some quantitative and qualitative variables have been dealt with stochastic imputation method, assuming fully conditional specification (FCS method of the MI procedure of the SAS software). The largest number of missing values (14,5%) was registered for the single question adopted to collect an approximative monthly total net household income. The approximative values collected may lead to a bracket distribution, as follows: [0-600 euro]; [600-700]; [700-900]; [900-1100]; [1100-1300]; [1300-1500]; [1500-1700]; [1700-1900]; [1900-2250]; [2250-2750]; [2750-3500]; [3500-4500]; [4500-5500]; [5500-6500]; [6500-8000]; [8000-10,000]; [10,000 and more]. Continuous values within each bracket have been imputed considering the kernel density estimation of the distribution reported in Figure 1. Based on the total household disposable income, equivalised income was obtained with the OECD-modified equivalence scale.

Figure 1 – Distribution and Kernel Density for the Equivalised Household Income (red_eq)



Source: Authors' elaboration on sample surveys data 2021

2.3. Multidimensional and Fuzzy Measure Computation

Based on the collected data, the multidimensional and fuzzy approach (Betti *et al*., 2006; Betti *et al*., 2021) is applied to compute poverty and deprivation/vulnerability measures, in a wider and more comprehensive perspective and overcoming the binary classification. So that, instead of identifying people as poor or non-poor in a crisp way, the approach allows to obtain a degree of membership as measure of the intensity of vulnerability or deprivation. Fuzzy set theorists consider that poverty is conceptually a vague predicate, and that fuzzy set approach deals systematically with the vagueness and complexity of multidimensional poverty (Chiappero-Martinetti, 2006; Qizilbash, 2006), similarly we can state for vulnerability or deprivation. Betti and Verma (2008) and Betti et. al (2015) proposed and updated the fuzzy measures based on the seminal contributions of (Cerioli, Zani, 1990; Cheli, Lemmi, 1995).

In the empirical analysis, to compute the fuzzy measure of vulnerability/deprivation, we consider eleven binary deprivation indicators focusing on households' current situation (September 2021). The indicators are based on the standard questions as regard to affordability: such as affordability to eat nutritional meals, to keep household adequately warm, to cover costs for health, to cover costs for

Table 1 – Factor Loadings and Variance Explained. Estimates Obtained Using Maximum Likelihood Estimation and Varimax Rotation

Variable	*Dimension1*	*Dimension2*	*Dimension3*	*h2*[*]	*u2*[**]	*Com*[***]
Meals with meat	0.67	0.14	0.29	0.55	0.453	1.5
Afford one week holiday	0.47	0.21	0.19	0.30	0.701	1.7
Household adequately warm	0.33	0.17	0.09	0.14	0.855	1.7
Health	0.45	0.20	0.21	0.29	0.713	1.8
Education	0.25	0.94	0.12	0.95	0.045	1.2
Transport	0.33	0.36	0.15	0.26	0.742	2.4
Children	0.27	0.86	0.13	0.84	0.161	1.2
Ricreative	0.67	0.17	0.21	0.52	0.476	1.3
Unexpected €800 expense	0.26	0.15	0.67	0.53	0.466	1.4
Unexpected €2000 expense	0.20	0.12	0.97	1.00	0.005	1.1
Unexpected €5000 expense	0.33	0.10	0.57	0.45	0.554	1.7
SS loadings	1.983	1.956	1.888			
Proportion Var	0.180	0.178	0.172			
Cumulative Var	0.180	0.358	0.530			

Notes: RMSEA = 0.044. Kaiser-Meyer-Olkin overall MSA = 0.81; [*]Amount of variance in the item/variable explained by the (retained) factors; [**]Residual (1-h2); [***]Item Complexity.
Source: Authors' elaboration

one week holiday, to cover costs for cinema, theatre, eating out once a month, to cover costs for transport, for children clothes, toys, specific children food); to cover costs for education such as taxes, books and materials and finally and then ability to cope with unexpected expenses of different amount. There is no need to rescale the items, as they are already binary variable assuming values 0 or 1.

The dimensions of deprivation have been investigated by an exploratory factor analysis (see Table 1) to identify the hidden dimensions of the multidimensional poverty. The three factors extracted accounted for 53% of the total variance. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy equal to 0.81 indicates that the factor analysis method is suitable for the collected data. Successively the latent structure identified has been validated using a Confirmatory Factor Analysis (CFA). The interpretation of latent dimensions identified are introduced in Table 2. The dimension 1 refer to "Inadequate Basic needs and non-inclusive lifestyle" indeed the indicators involved in the computation of this latent dimension, refer to the lack of possibility of satisfying basic needs and possibility of living with an inclusive lifestyle.

Table 2 – Dimensions (Membership Function) and Indicators

Dimensions	*Indicators*
1. Inadequate basic needs and non-inclusive lifestyle (FS1)	Meals with meat or fish // Household adequately warm // cover costs for health// cover costs for 1 week holiday// cover costs for cinema, theatre, eating out once a month
2. Children specific deprivation (FS2)	Costs for: transport// children (clothes, toys, child's food)// education (taxes, books and materials)
3. Financial vulnerability (FS3)	Inability to cope with unexpected expenses: 5000, 2000, 800 Euros

Source: Authors' elaboration

The dimension 2 presents very high factor loadings for items regarding expenditure for children needs and education, therefore we interpret it as an indicator of "Children specific deprivation" (see Carraro, Ferrone, 2020; Benedetti *et al*., 2020 for a related study on this topic).

The dimension 3 involves expenditure inability to cope with unexpected expenses, therefore we interpret it as an indicator of "Financial vulnerability", indeed, we use to say that households are financially vulnerable, if they have not enough assets to face an event that decreases incomes or increases expenses (Prieto, 2022).

Then, we calculate weights of individual items of deprivation within each dimension and the scores within each dimension (Betti et. al., 2015). Finally, we obtain the membership function to the sets of deprived/vulnerable for each dimension, meaning a quantitative specification of the propensity to deprived/vulnerable of each household, ranging in [0-1], where 0 means that the household does not belong to the set of deprived/vulnerable for a given dimension and 1 means that the household belongs completely to it.

In the following analysis, we refer to the Head Count Ratio (HCR) as traditional measure of economic poverty and to FS1, FS2 and FS3 as the membership functions to the set of deprived/vulnerable, according to the three dimensions introduced in Table 2.

2.4. Small Area Estimation

In this sub-section, we briefly discuss on the target domains of the analysis, the kit of information necessary to perform small area estimation, and the standard of data quality. As regards to the target domains of the analysis, we consider the Tuscan provinces, and a non-standard territorial classifications obtained as an aggregation of functional geographies, specifically grouping according to economic characterization the so called Local Labour Market Areas. Such grouping, in six different areas, refers also to the levels of employment and of the remuneration of productive factors (labour and capital) and consequently to different level of wellbeing. In detail the six area are the following: Cities, the urban territories, with an important presence of the tertiary sector to businesses as well as to persons; Made in Italy, manufacturing areas based on the traditional production vocations of textiles, leather, leather goods, furniture, etc.; Other Industry, manufacturing areas not belonging to the Made in Italy sector; Seaside Tourism, coastal territories having a seasonal tourist characterization; Agritourism area, promoting sustainable agriculture and ecological tourism; Internal Areas Northern Apennines, the furthest area from centres, lacking of essential services.

These tables (3 and 4) show that in some domains, the sample size is likely too small to produce reliable estimates at local level. Indeed, in many cases, direct estimates will not be sufficiently reliable, and we try to improve them by using small area estimation.

The idea behind small area estimation is to borrow strength from auxiliary variables to obtain indirect estimators that may exhibit a lower mean squared error than that of the direct estimator. Many small area models have been proposed in the literature (Rao, Molina, 2015), in this paper, given the availability of unit-level data we make use of the Fay-Herriot model (FH) (Fay, Herriot, 1979).

Before being able to estimate the Fay-Herriot model, we need to prepare aggregate (area-level) data. For this purpose, the appropriate auxiliary variables are based on administrative data (Istat-IRPET), therefore they are measured without error (see Arima *et al*., 2015; Bell *et al*., 2019 for a dissertation on when there is error measurement in the covariates). Then we compute the direct estimates and the corresponding estimates of the variance in each area. The variances are estimated using the bootstrap (*laeken R package*), as we do not have information on the sampling design. These estimated variances are the basic inputs of the Fay-Herriot model. To estimate the model, we use the *sae R package* (*function mseFH*), to produce both point estimates of the deprivation measures and the related Mean Squared Error (MSE). The command requires the specification of the linking model, and the specification of the variance of the direct estimates. In our estimation, we regress each direct estimates on the set of identified covariates.

Finally, to assess the accuracy of the results based on the survey data, we use the coefficient of variation (CV), as it is a standardized measure of the sampling variability. Statistics Canada[1] provides guidelines for publication related to the uncertainty of estimates specifying the following levels of data quality: excellent (0-5%), very good (5-15%), good (15-25%), acceptable (25-35%), (>35%) use with caution. Nevertheless, many Official Statistical Agencies do not publish estimates with coefficient of variation higher than 20%.

1. Statistics Canada – National Travel Survey (www23.statcan.gc.ca).

Table 3 – Sample Size by Province

Province	*Sample size*
Prato	83
Massa	94
Livorno	164
Grosseto	166
Pistoia	175
Arezzo	207
Lucca	263
Siena	320
Pisa	336
Firenze	691

Table 4 – Sample Size by Area

Area	*Sample size*
5. Agritourism area	67
6. Internal Areas Northern Apennines	72
4. Seaside Tourism	270
3. Other Industry	614
2. Made in Italy	725
1. Cities	751

Source: Authors' elaboration

3. Results

3.1. Regional Level

According to IRPET (2022) the households in absolute poverty in Tuscany went from 4.47% to 5.08% between 2019 to 2021, thanks to the interventions put in place to protect families to contain the effects of the pandemic. Referring to a relative measurement approach, the estimated head count ratio computed on the data collected, using the Eurostat-type poverty line (60% of the median equivalised income), is equal to 11.58% at regional level.

The high rate of home ownership in Italy keeps resisting despite some economic difficulties, indeed, the Italian Revenue Agency and the Finance Department of the Ministry of Economy state that, three out of four Italian families own the home they live in. According to our estimation on the data collected, in Tuscany this rate is still higher indeed, we estimate that the 86.7% of the Tuscan families own the home they live in; among them only a percentage equal to 8.9 have a mortgage to pay.

Shifting our perspective towards the subjective approach, we present some descriptive results at regional level, to have a general picture of the perceived economic situation of the inhabitant families.

Specifically, analysing the data collected by the question: "Taking into account your actual income, how can your household make ends meet? With great difficulty/some difficulty/difficulty/fairly easily/easily/very easily?" (Ravallion, 2014, 2015). We can observe (Table 5) that more than half of the households (53.06%) make end meet facing at least "Some difficulty".

Moreover, one out of eight households (see Table 6) should define the economic situation of her/his family as very poor or poor. This amount is very close to the estimated head count ratio (11.58%).

Observing Table 7, we can realize that for nearly 33% of the households the economic situation got at least "slightly worsened" with respect to the pre-pandemic period (2019).

As of what the households expect for the coming twelve months (i.e. Autumn 2022), and analysing the distribution of the households expectations, conditioned to the "ability to make end meet" (see Figure 2) we notice that the difficulties to make ends meet increase as it does the percentage of households expecting worsening for the next months. Thus, we can state that the actual difficulties, even if strongly influenced by the contingent situation of the pandemic are perceived as a middle/long term situation.

Table 5 – Subjective Poverty: Ability to Make Ends Meet (%)

Making ends meet…	*%*
with great difficulty	7.15
with difficulty	11.40
with some difficulty	34.51
fairly easily	30.07
easily	14.61
very easily	2,26

Table 6 – As Regard to Your Current Economic, You Could Define…

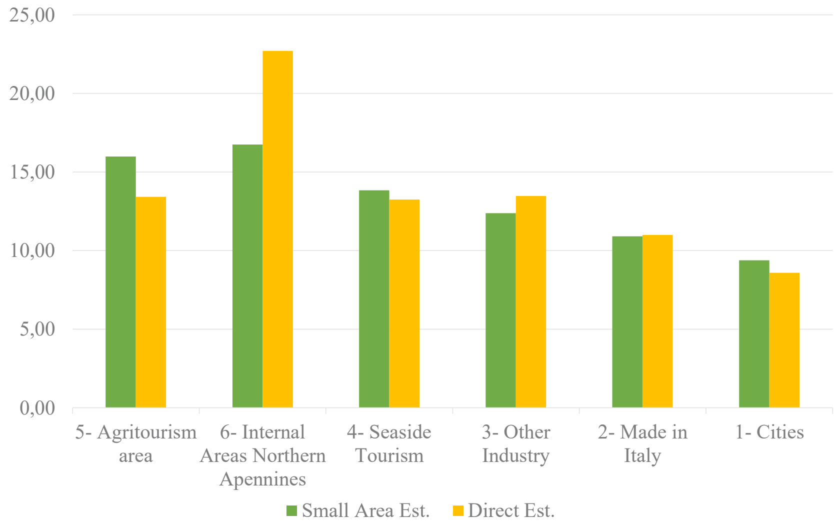
…your household as …	*%*
very rich/rich	7.15
neither rich nor poor	85.07
very poor/poor	12.24

Table 7 – Comparing Current Economic Situation with Respect to 2019

The economic situation has…	*%*
improved	5.66
unchanged	61.46
slightly worsened	23.50
greatly worsened	9.38

Source: Authors' elaboration

Figure 2 – Economic Expectations



Source: Authors' elaboration

However, monetary poverty and questions related to the perceived economic situations can capture a household's ability to meet critical situation like the pandemic one, but surely it does not capture all forms of deprivation. For this reason, in the following sections our analysis considers also non-monetary multidimensional and fuzzy measures of deprivation/vulnerability.

3.2. Small Area Analysis

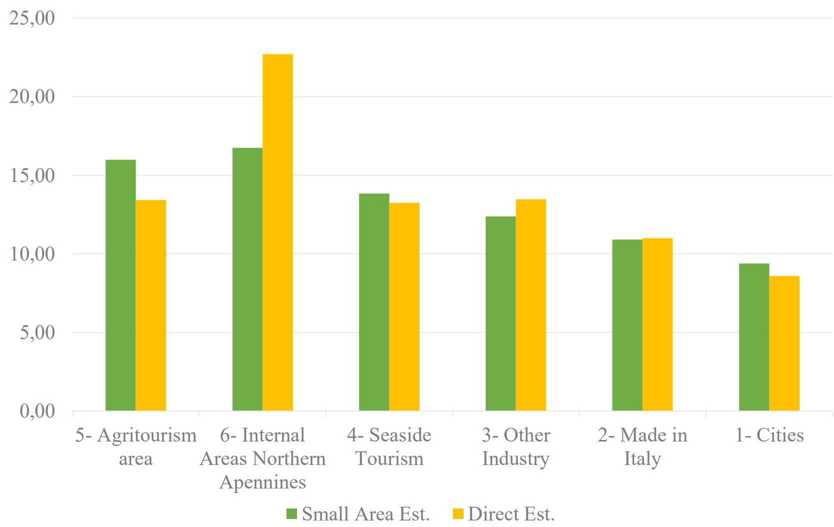
The estimation of the percentage of households living in poverty conditions (Head Count Ratio) is based on the equivalised household income. Moving the focus to the multidimensional and fuzzy dimensions, the indicators have been estimated at province level and at specific area level through the application of the Fay Harriot models, obtaining the Empirical Best Linear Unbiased Predictor (EBLUP). All EBLUPs estimates, from now on, labelled as Small Area Est., are compared with the correspondent direct estimates (labelled as Direct Est.). Moreover, to state gains in the accuracy of the small area level estimates we compared the coefficient of variation (CV) of the Small Area Estimator with the respective direct estimates' coefficient of variation. The results of the small area level estimates were obtained using the sae R-package (Molina, Marhuenda, 2015).

Let's start from the six areas previously introduced. To estimate the Fay-Herriot model for the Head Count Ratio and for the membership functions to the set of deprived/vulnerable, according to the three dimensions introduced in Table 2, the auxiliary variables considered are: percentage of people employed, for the estimation of the Head Count Ratio, and the percentage of people receiving citizenship retirement benefits, for the membership function (labelled as FS1, FS2, FS3).

The estimated Head Count Ratios (Figure 3) show that "Cities" and "Made in Italy" areas have less households living in poverty conditions while "Internal Areas Northern Apennines" and "Agritourism area" are the poorest areas. Interestingly, the Small Area estimate of "Internal Areas Northern Apennines" revises downwards significantly the direct estimate. Figure 4 shows that the gains in efficiency of the Small Area Estimators tend to be larger for areas with smaller sample sizes. Thus, Small Area estimates based on Fay-Herriot model seems more reliable than direct estimates.

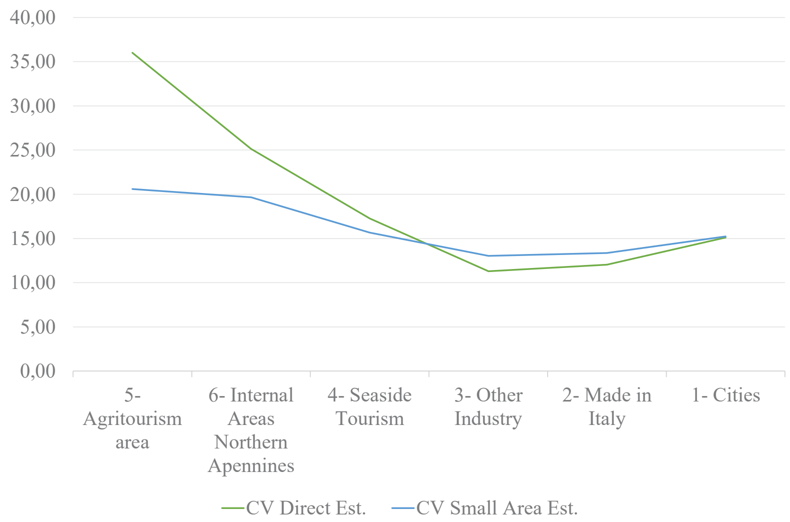
The most dominant dimension of deprivation for all the considered areas is "Inadequate basic needs and non-inclusive lifestyle", whose membership function is FS1 (Figure 5); it is followed, in a less extent, by children-specific vulnerability (FS2, Figure 5). The "Cities" area is the one that experiences significantly less the dimension of financial insecurity (FS3, Figure 5), maybe it is because households have enough assets to face an event, like the pandemic, that

Figure 3 – Small Area Estimates and Direct Estimates for Head Count Ratio by areas (2021). Areas are Sorted by Increasing Sample Size



Source: Authors' elaboration

Figure 4 – Coefficients of Variation (CV) for Small Area Estimators and Direct Estimators of the Head Count Ratio by areas (2021). Areas are Sorted by Increasing Sample Size



Source: Authors' elaboration

Figure 5 – Membership Functions (FS1, FS2, FS3) to the Set of Deprived/ vulnerable, According to the Three Dimensions (2021). Area Level

Source: Authors' elaboration

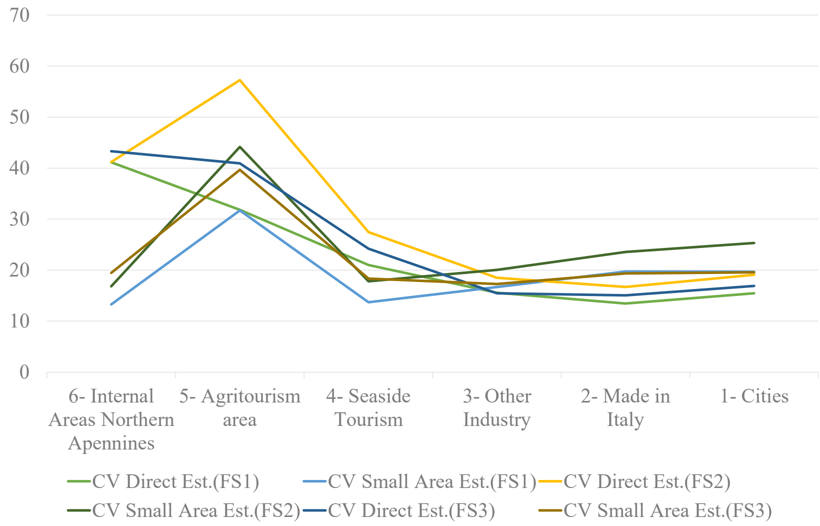
in many cases decreases incomes. This result is coherent with the Head Count Ratio (Figure 3), that for "Cities" is significantly lower than in the other areas.

Figure 6 shows again that we can obtain the major gains in efficiencies in the areas having smaller sample size, although, in the most sampled areas, the mean squared error of the small area estimators are sometimes larger than that of the direct estimate. However, this is not necessarily a problem as the estimates in these areas have good quality.

As regards to province breakdown, we can observe (see Table 5) that Prato and Massa-Carrara are the provinces presenting the smallest sample sizes, while Florence and Pisa have the two greatest sample sizes.

To estimate the Fay-Herriot model for the Head Count Ratio and for the membership functions to the set of deprived/vulnerable, according to the three dimensions considered in the analysis, the auxiliary variables used to obtain small area estimates are the weighted 10-th percentile of the income distribution of the total income distribution, for Head Count Ratio, and the percentage of households who own the house where they live, for the membership functions FS1, FS2, and FS3.

Figure 6 – Coefficients of Variation (CV) for Small Area Estimators and Direct Estimators of the Membership Functions by areas (2021). Areas are Sorted by Increasing Sample Size



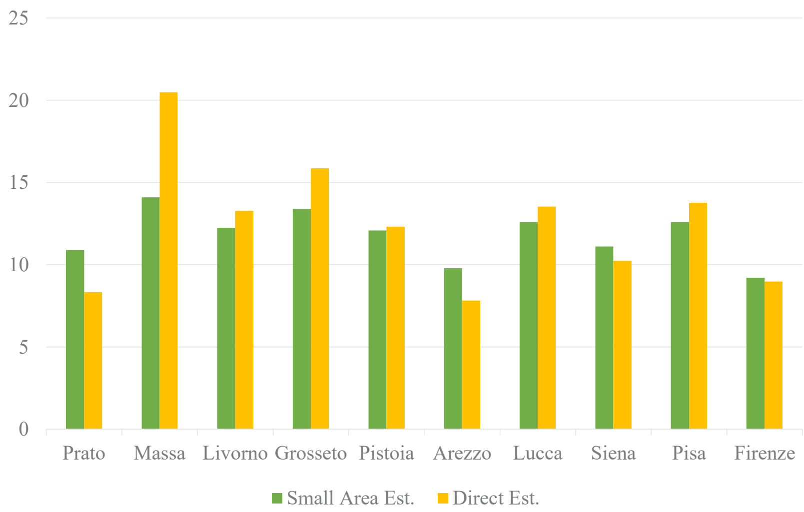
Source: Authors' elaboration

In Figure 7, we can observe that the Small Area Estimates track the direct ones, but are significantly less volatile. According to the Small Area Estimates we observe (Figure 7) that Firenze, Arezzo, Prato and Siena, present Head Count Ratio values below the regional one (HCR= 11.58%), while Massa and Grosseto present larger values.

Observing Figure 8, we can state that three provinces (Prato, Arezzo, and Siena) present Direct Estimates for Head Count with just acceptable Coefficients of Variation (ranging approximatively in 25%-35%), whereas the Coefficients of Variation of the Small Area Estimates do not exceed 22% for any of the areas (very good or good quality).

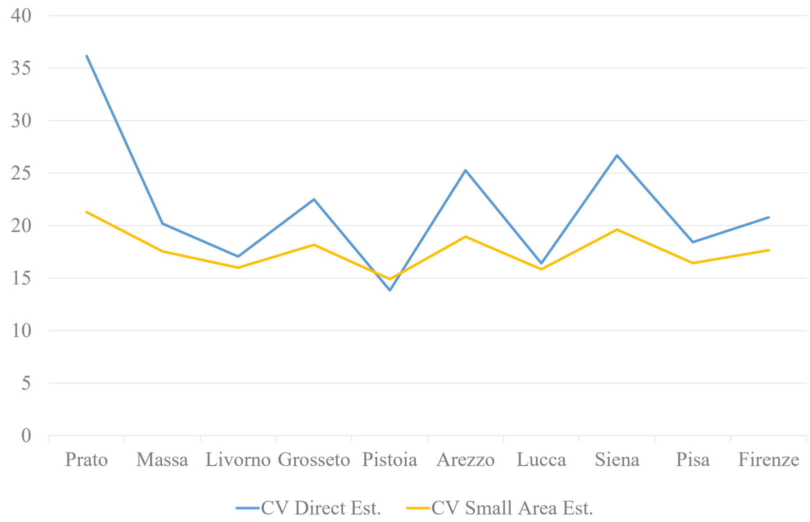
Regarding non-monetary dimensions, deprivation in basic needs and inclusive lifestyle is the dimension dominating (see Figure 9). For this dimension, the less deprived province is Prato, followed by Arezzo. The ten provinces show homogeneous deprivation measures as regard to dimension 2. Financial vulnerability is a dimension showing the lowest intensity and, it is particularly contained in the provinces of Arezzo and Prato. These provinces, with Florence are also those presenting the lower values for the monetary poverty.

Figure 7 – Small Area Estimates and Direct Estimates for Head Count Ratio by Provinces (2021). Areas are Sorted by Increasing Sample Size



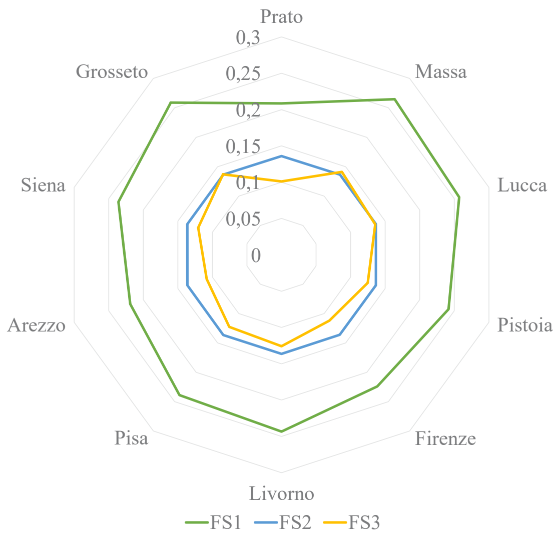
Source: Authors' elaboration

Figure 8 – Coefficients of Variation (CV) for Small Area Estimators and Direct Estimators of the Head Count Ratio by Provinces (2021). Areas are Sorted by Increasing Sample Size



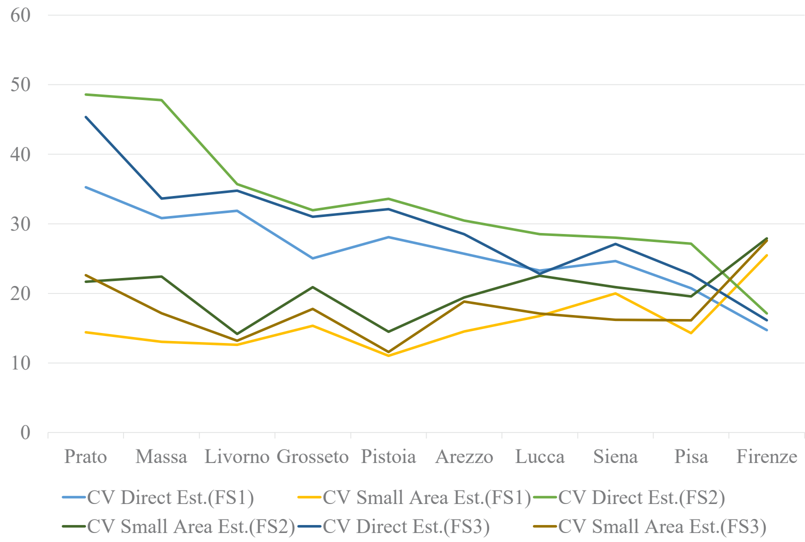
Source: Authors' elaboration

Figure 9 – Membership Functions (FS1, FS2, FS3) to the Set of Deprived/ vulnerable, According to the Three Dimensions (2021). Province Level



Source: Authors' elaboration

Figure 10 – Coefficients of Variation (CV) for Small Area Estimators and Direct Estimators of the Membership Functions by Provinces (2021). Provinces are Sorted by Increasing Sample Size

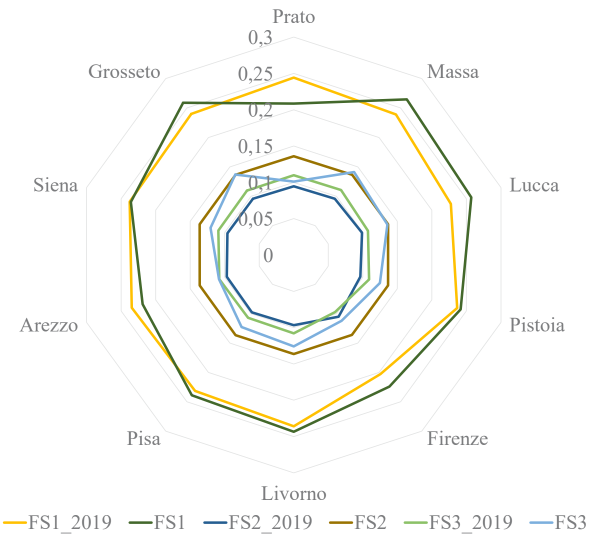


Source: Authors' elaboration

Figure 10 shows the Coefficients of Variation computed for the direct estimates an for those obtained by small area methods. The small area level methods provide estimations with a lower Coefficients of Variation in all the provinces with exception of Florence. This happens for all the measures of non-monetary poverty that we consider. The reason could be the variability of the indicators in Florence, indeed the variance of estimation is a function of the estimation itself, so that we expect larger uncertainty when the estimation focuses on rare events (Wolter, 2007). However, the Coefficients of Variations related to the small area estimation do not exceed 23% for any of the provinces (very good or good quality standard).

Finally, we consider again the multidimensional and fuzzy measures FS1, FS2, FS3, based on the eleven binary deprivation indicators focusing on households' current situation (September 2021) and we adopt the same method to compute analogous measures FS1_2019, FS2_2019, FS3_2019, given that to the respondent was proposed such a question for the period 2019. The results, at province, are shown in the spider graph (Figure 11). We can observe that in general all the deprivation lines for 2021 are external to the correspondent line for 2019 meaning that the deprivation for 2021 is larger than 2019 as it was expected.

Figure 11 – Membership Functions (FS1, FS2, FS3) to the Set of Deprived/vulnerable, According to the Three Dimensions (2021 vs 2019). Province Level

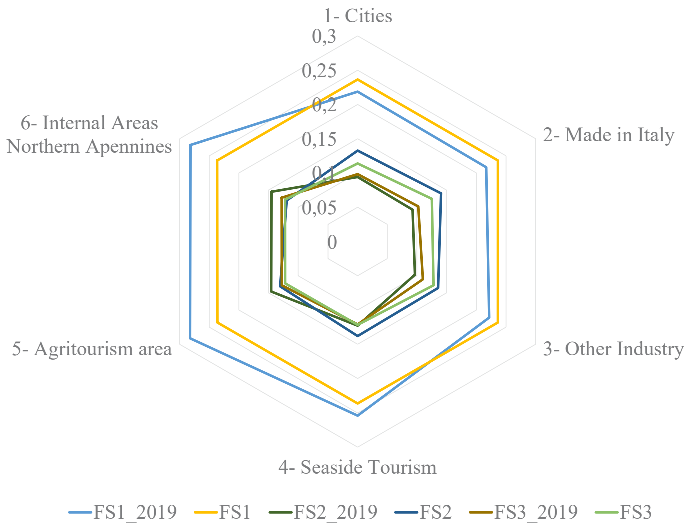


Source: Authors' elaboration

At province level, as regard to the intensity, we can observe that: in general, the higher level of deprivation is registered on the dimension, Basic Needs and Inclusive Lifestyle Vulnerability; for all the provinces out of Arezzo and Prato, Basic Needs and Inclusive Lifestyle Vulnerability is increased between 2019 and 2021; for all the provinces the Children specific Vulnerability has increased between 2019 and 2021; as regard to the Financial Vulnerability, for all the provinces out of Arezzo and Prato, the intensity of the vulnerability is increased between 2019 and 2021, while for Arezzo and Prato it is unchanged.

Observing the results of the comparison 2021 vs 2019 at area level (Figure 12), we can state that: once again, the higher level of deprivation is registered on the dimension Basic Needs and Inclusive Lifestyle Vulnerability; for all the areas, out of Seaside Tourism, Agritourism area, Internal Areas Northern Apennines, Basic Needs and Inclusive Lifestyle Vulnerability is increased between 2019 and 2021; for all the areas out of Agritourism area, Internal Areas Northern Apennines the Children specific Vulnerability has increased between 2019 and 2021; as regard to the Financial Vulnerability, for all the areas out of Internal Areas Northern Apennines, the intensity of the vulnerability is increased between 2019 and 2021, while for Arezzo and Prato it is unchanged.

Figure 12 – Membership Functions (FS1, FS2, FS3) to the Set of Deprived/vulnerable, According to the Three Dimensions (2021 vs 2019). Area Level



Source: Authors' elaboration

4. Further Remarks

The world-wide events that are marking the history of our time, such as the Covid-19 pandemic, the energy crisis, and the rise in the prices of certain essential foodstuffs have posed new challenges for Italy, among which the rise of new forms of inequalities and social and economic vulnerability that have a crucial effect on people wellbeing. The state of the art has highlighted shortcomings in the existing multidimensional poverty studies and a gap in up-to-date data on the effects of the recent crises. Tuscany has financed the sample survey 2021 on which the analysis conducted in this paper are based, and a second sample survey one year after (October 2022) where have been collected also data related to the impact of the energy crisis and the rise in the prices. The aim is to assess whether pockets of vulnerability are further extended in this last phase, despite the policies to combat poverty of the last three years. In this situation, the risk is that even if the families have not fallen below of the poverty threshold, their economic behaviour could be curbed, by the limited availability of resources but also by fear for the near future. These data will be essential for local governments to set up recommendations to policy makers on appropriate policy interventions for fighting poverty and social exclusion. Guidelines and recommendations will be a useful for designing new policies for the poor and vulnerable groups, with the aim of i) addressing the gaps in social protection of citizens and ii) making, at least the regional welfare system more resilient to future shocks through more effective and flexible policies.

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Vulnerabilità alla povertà delle famiglie toscane durante la pandemia da Covid-19

Sommario

La Banca mondiale e altre istituzioni internazionali hanno sottolineato l'importanza di studiare la natura mutevole della povertà e il monitoraggio delle condizioni di povertà causate dalla pandemia da COVID19. In questo lavoro, l'obiettivo è stimare le misure di povertà monetaria e non monetaria in Toscana, a due diversi livelli subregionali. Tutto ciò è stato possibile, grazie a una fonte di dati originale ottenuta attraverso un'indagine ad hoc sul tema della vulnerabilità e povertà, pianificata e condotta nel settembre 2021 dall'Istituto Regionale per la Pianificazione Economica della Toscana (IRPET) in collaborazione con l'Università di Siena. L'indagine campionaria è stata effettuata diciotto mesi dopo l'inizio della pandemia e alcune delle variabili raccolte riguardavano aspetti della percezione soggettiva della povertà. Inoltre, la rilevazione ha riguardato una serie di indicatori di deprivazione/vulnerabilità riferiti alla situazione attuale delle famiglie (settembre 2021) ed al periodo precedente alla pandemia (2019), per consentire un confronto tra i due periodi. Nell'analisi empirica, si stima la percentuale di famiglie che vivono in condizioni di povertà, a due diversi livelli subregionali, secondo l'approccio tradizionale e secondo un approccio multidimensionale e fuzzy. Valutiamo la qualità di queste stime, concludendo che per alcune piccole aree l'accuratezza non risultava sufficiente, pertanto, abbiamo fatto ricorso a metodi di stima per piccole aree.

Part 2

Socio-Economic Transformations: Measurement Tools

Territorial Mapping of EU Funding Programmes for Research and Innovation Activities

Andrea Conte, Anabela M. Santos**

Abstract

This chapter aims to provide a comprehensive overview of the primary features of European Union (EU) funding programs across thematic areas, focusing on the challenges that policymakers face with regards to the territorial allocation and mapping of EU funds directed towards research and innovation (R&I) activities across regions in the context of place-based policies. In doing so, this chapter highlights several methodological challenges faced by analysts, including the occurrence of multiple taxonomies and the lack of uniform data coverage for certain policies and across different territorial units of analysis. To address these methodological issues, this chapter introduces a new tool developed by the European Commission – the Territorial Economic Data viewer – with the purpose of overcoming these challenges. Furthermore, this chapter provides practical examples of the tool's usefulness in policy support, particularly with regards to the mapping of low-carbon technologies in the context of the European Union's green deal initiative.

1. Introduction[1]

Innovation plays a pivotal role in advancing regional economic development by promoting the emergence of new industries and products, fostering productivity growth (Mohnen, Hall, 2013) and creating job opportunities (Ciriaci *et al.*, 2016). However, the innovation process can be risky (Mazzucato, 2013) and expensive, typically demanding significant investments in research and development (R&D) activities. Such expenses can pose substantial challenges for businesses, especially in regions with limited private sector investment. In this regard, public support for R&D can serve as a crucial source of funding for innovative firms (Guellec, Van Pottelsberghe De La Potterie, 2003), providing a

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1. The views expressed are purely those of the author(s) and may not in any circumstances be regarded as stating an official position of the European Commission.

much-needed boost to their development efforts and benefiting the economy as whole.

This chapter describes how complex and challenging an accurate territorial monitoring of public support – especially through European Union (EU) funding targeted to R&D and innovation activities – can be for policymakers. For this purpose, it serves a fourfold purpose. Firstly, it aims to provide a comprehensive overview of the structure of the EU budget, with a particular emphasis on funding lines that are focused on regional development and innovation policy, and how they may interact with each other. Secondly, it highlights the difficulties faced by policymakers in monitoring these funding lines and the challenges of linking data across multiple taxonomies and governance levels. Thirdly, it presents a new tool developed by the European Commission, the Territorial Economic Data viewer (TEDv), which has been designed to overcome these obstacles. Fourthly, this study aims to demonstrate the usefulness of text mining analysis in supporting policy monitoring by providing a more accurate analysis compared to existing taxonomy.

The EU budget evolves over time through a seven-year budgetary cycle known as the Multiannual Financial Framework (MFF). Understanding its structure is crucial for policymakers and stakeholders to effectively plan and implement policies that promote economic growth and development. This chapter sheds light on the key elements of the budget, including expenditure categories and governance allocation mechanisms for regional development and innovation policies.

One of the challenges in monitoring national and EU funding is the lack of a centralized data repository. Policymakers must navigate through a plethora of data sources, taxonomies, and governance levels to obtain the information they need. This task is further complicated by the fact that data is often presented in different formats and may be difficult to compare across regions.

The Territorial Economic Data viewer (TEDv), developed by the European Commission (EC), is a tool that addresses these challenges. The tool integrates multiple data sources and presents the information in a user-friendly format that policymakers can use to make informed decisions. The tool's primary focus is now on regional research and innovation policies, but it can be potentially extended to other policy areas, such as environmental and social policy, following new policy priorities established over time.

This chapter provides practical examples of how the TEDv has been developed to better inform policy making. As an example, the tool has proven useful in mapping low-carbon technologies in the context of the EU's Green Deal initiative. By overcoming limitations on data provision and, for instance, providing policymakers with detailed information on the deployment of low-carbon technologies across different regions, the tool can help identify areas where additional investment and support may be needed.

2. EU R&I Funds and the Multi-Annual Financial Framework (MFF)

The Multiannual Financial Framework (MFF) for the current period 2021-2027 is the long-term budget of the European Union (EU), outlining the EU's spending priorities and financial limits for the current financial cycle. The total size of the MFF for the 2021-2027 period is set at €1.074 trillion in 2018 prices (€1.211 trillion in current prices). After the emergence of the Covid-19 pandemic, the Commission presented a recovery strategy on May 27, 2020. This proposal included updated suggestions for the MFF and own resources, along with the establishment of a new recovery instrument, known as Next Generation EU, which has a total budget of €750 billion. The MFF was finally adopted in December 2020[2].

The MFF is divided into seven Headings. Research and Innovation funding is mostly channelled via Heading 1 (Single Market, Innovation, and Digital – SMID) and Heading 2 (Cohesion, Resilience and Values – CRV)[3].

1. The SMID Heading has a total budget of €161 billion (including €11.5 billion from NGEU) and it aims to promote economic growth, innovation, and digital transformation across the EU by funding major initiatives such as:
   - The Horizon Europe research programme (called Horizon 2020 during the MFF 2014-2020) with a stronger focus on research in health, resilience, and the green and digital transitions (total budget of €99.5 billion (including €5.41 billion from NGEU).
   - The InvestEU (called Investment Plan for Europe, the Juncker Plan, during the MFF 2014-2020) aims to mobilize public and private investments by using the EU budget as a guarantee. It is structured along three main instruments/activities: (a) the Fund, (b) the Advisory Hub (responsible for providing technical advice to investment projects that require financing) and (c) the Portal (aiming at matching project demand with potential investors). InvestEU's four main areas of intervention are: (i) sustainable infrastructure (with a budget of €9.9 billion); (ii) research, innovation, and digitalization (€6.6 billion); (iii) SMEs (€6.9 billion); and (iv) social and skills investments (€2.8 billion) for a total budget of €26 billion (including €6.07 billion from NGEU).
2. The CRV is the biggest Heading of the 2021-2027 EU MFF with a total budget of €1203 billion due largely to the inclusion of €776.5 billion from NGEU. The main investment programmes under this category aim to promote sustainable territorial development, make Europe more resilient to the various challenges

2. https://www.europarl.europa.eu/factsheets/en/sheet/29/multiannual-financial-framework.
3. The MFF comprises five additional categories; namely Natural Resources and Environment (Heading 3), Migration and Border Management (Heading 4), Security and Defence (Heading 5), Neighbourhood and the World (Heading 6), and European Public Administration (Heading 7).

ahead (from health to skills etc.) as well as strengthen the cohesion among EU Member States and thus reducing disparities across EU territories (regions and Member States). Within this Heading, the major funding initiatives are:

- The new Cohesion Policy 2021-2027, with a total budget of €392 billion, includes the European Regional Development Fund (ERDF), the Cohesion Fund (CF), the European Social Fund Plus (ESF+), and the Just Transition Fund (JTF).
- The NGEU (€776.5 billion) split between the Recovery and Resilience Facility (€723.82 billion), REACT-EU (€50.62 billion), and RescEU (€2.0 billion), all in current prices.

2.1. Horizon Europe

Horizon Europe (HE) is the European Union's (EU) flagship research and innovation program. It is the successor to the Horizon 2020 program and has a budget of €95.5 billion for the period spanning from 2021 to 2027. As a result, HE is the largest trans-national research and innovation program in the world. Its budget – which includes €5.4 billion from the NGEU targeting the so-called twin (green and digital) transition – is distributed across four pillars and fifteen components. These four pillars are:

- Excellent science (€25.01 billion). This pillar stresses the importance of fundamental research and aims to support world-class excellence in science across Europe. It includes funding for the European Research Council (ERC), Marie Skłodowska-Curie Actions (MSCA) as well as funding for research infrastructures.
- Global Challenges and European Industrial Competitiveness (€53.52 billion). This pillar aims to address a wide range of global challenges (i.e. health, climate, civil security) and promote European industrial competitiveness by reinforcing technological and industrial capacities through clusters. It identifies five EU-missions[4] and includes seven components; namely, (a) health, (b) culture, creativity and inclusive society, (c) civil security for society[5], (d) digital, industry and space , (e) climate, energy and mobility[6], (f) food,

4. These are the EU Missions established with a 2030 target: (a) Adaptation to Climate Change: support at least 150 European regions and communities to become climate resilient, (b) Cancer: working with Europe's Beating Cancer Plan to improve the lives of more than 3 million people; (c) Restore our Ocean and Waters, (d) 100 Climate-Neutral and Smart Cities, (e) A Soil Deal for Europe: 100 living labs and lighthouses to lead the transition towards healthy soils.
5. Research and innovation activities funded by Horizon Europe focus exclusively on civil applications. A budget of €8 billion for 2021-2027 is instead dedicated to the European Defence Fund (EDF) for collaborative defence research and collaborative capability development projects.
6. Over 35% of Horizon Europe spending should contribute to climate objectives.

bioeconomy, natural resources, agriculture and environment as well as (g) non-nuclear direct actions of the Joint Research Centre (JRC).

- Innovative Europe (€13.60 billion). This pillar aims to make Europe a leader in market-creating innovation and to better develop the overall European innovation landscape. As such, it includes funding for three components; namely (a) the European Innovation Council (EIC), which aims to sustain breakthrough and disruptive technologies through its funding schemes[7] and (b) the European Institute of Innovation and Technology (EIT), which mostly focuses on supporting the cooperation activities under the different thematic Knowledge and Innovation Communities (KICs). Finally, (c) the European innovation ecosystems where the objective is to create inclusive, efficient and interconnected networks potentially stimulating innovation and supporting the scalability of businesses.
- Beyond the three implementing pillars above, Widening Participation and Strengthening the European Research Area (ERA) (€3.39 billion) provides support to EU Member States in their efforts to reform and enhance their national research and innovation potential and promote a better circulation of researchers, scientific knowledge and technology in the ERA. By allocating dedicated funding and implementing targeted R&I actions in lagging EU regions, this pillar directly contributes to reducing the existing innovation gap by increasing their participation in R&I activities and enhancing their capacity for research and innovation[8].

The issue of tackling the innovation divide and evaluating the impact of policies goes beyond the scope of the Widening Participation initiatives only. On the one side, Horizon Europe might strongly contribute to enhance national and regional innovation capacity by encouraging collaboration, partnership, the exchange of cutting-edge knowledge, expertise, and providing a significant additional funding to all innovation actors (public and private stakeholders, mono-beneficiaries and research consortia) – especially to those operating in territories that may otherwise have limited access to these resources[9]. Moreover, the program's focus on cross-cutting issues such as societal challenges as well as its mission-oriented

7. This funding is channelled through the EIC Pathfinder, the EIC Transition and EIC Accelerator. 70% of the budget of the European Innovation Council should be allocated to small and medium size enterprises.
8. Examples of initiatives under "widening participation and spreading excellence" include (a) pathways to Synergies, (b) Teaming for Excellence, (c) Twinning Green Deal, (d) ERA Chairs, (e) Twinning Bottom-Up, (f) European Excellence Initiative, (g) Hop on Facility, (h) ERA Talents, (i) Dissemination & Exploitation Support Facility, (j) Excellence Hubs.
9. HE promotes open science and innovation, making research data, publications and software accessible to the public. This approach might reduce regional innovation disparities by facilitating knowledge sharing, collaboration, and providing access to previously unavailable knowledge for researchers and innovators from less-developed regions.

approach, is likely to require a multidisciplinary approach and thus encourage collaboration between different actors, including researchers, companies, and public authorities, which can help to build regional innovation ecosystems and improve innovation performance. On the other side, while HE might have a positive impact on innovation in more developed regions, it's possible that it won't be as effective in promoting innovation in less-developed areas. This could be attributed to several factors, such as the limited reach of HE funding in these regions due to the weaker administrative and institutional capacity of research actors. Additionally, research actors in these regions may have a more narrow focus / specialisation on the topics related to HE calls and face greater competition. As a result, HE may result in inadvertently exacerbating the innovation gap between regions instead of bridging it.

The territorial impact of HE is difficult to anticipate – also because there is no ex-ante territorial allocation and the funding is assigned mainly through open and competitive calls for proposals. The program is implemented directly by the European Commission (direct management) in a way that it is aligned with the research and innovation priorities of the European Union and its Member States.

Horizon Europe is governed by the European Commission, which is responsible for coordinating and managing the program's strategic objectives and funding priorities. The European Parliament and Council of the European Union act as decision-makers, adopting legislation that sets out the program's objectives and budget and monitoring its implementation. The program includes a strategic planning process that involves the development of a strategic plan and work programs, which are periodically updated to reflect changing circumstances and stakeholder consultation. Co-programming with Member States and stakeholders is a key feature of Horizon Europe, ensuring alignment with national and regional research and innovation priorities and encouraging collaboration and partnership. To ensure the program's effectiveness, Horizon Europe has a comprehensive evaluation and monitoring system, including regular reporting on performance and impact and external evaluations of specific aspects of the program[10].

2.2. Innovation Funding under the European Structural and Investment Funds

As the investment policy of the European Union, Cohesion Policy aims to promote job creation, business competitiveness, economic growth, sustainable development, and enhance the quality of life of citizens in all EU regions and cities. To achieve these objectives, Cohesion Policy has been allocated €392 billion,

10. https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/horizon-dashboard.

representing almost one-third of the total EU budget for the period 2021-2027. The reduction to 5 policy objectives (compared to the 11 thematic objectives in the 2014-2020 period) is an important novelty of the new Cohesion Policy. The new pillars are the following:

1. a more competitive and smarter Europe
2. a greener, low carbon transitioning towards a net zero carbon economy
3. a more connected Europe by enhancing mobility
4. a more social and inclusive Europe
5. Europe closer to citizens by fostering the sustainable and integrated development of all types of territories

Differently from the previous MFF, Cohesion Policy is delivered during the 2021-2027 period through four specific funds contributing to the five different pillars[11]:

- The European Regional Development Fund (ERDF) aims to reduce regional disparities and promote economic, social, and territorial cohesion within the EU (main priorities: pillars 1 and 2). During the period 2021-2027, it will invest in creating a smarter, greener, better-connected, socially responsible Europe, with a focus on bringing citizens closer together.
- The Cohesion Fund (CF) provides assistance to EU Member States whose gross national income (GNI) per capita is below 90% of the EU-27 average, in order to promote economic, social, and territorial unity[12]. The fund primarily supports investments related to environmental protection and transport infrastructure networks, including the Trans-European Transport Network (TEN-T). Approximately 37% of CF's total financial allocation is expected to be allocated towards achieving climate goals (main priorities: pillars 2 and 3).
- The European Social Fund Plus (ESF+) (€99.3 billion) is the main investment tool in response to social challenges in the context of the implementation of the European Pillar of Social Rights[13] (main priority: pillar 4). The ESF+ integrates four funding instruments that were formerly separate during the 2014-2020 programming period: the European Social Fund (ESF), the Fund for European Aid to the Most Deprived (FEAD), the Youth Employment Initiative, and the European Programme for Employment and Social Innovation (EaSI).

11. During the 2014-2020 period, ESIF was made up of five funds, including ERDF, ESF, Cohesion Fund, EAFRD, and EMFF with a total budget of around €352 billion.

12. For the period of 2021-2027, the Cohesion Fund is applicable to Bulgaria, Czechia, Estonia, Greece, Croatia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Portugal, Romania, Slovakia, and Slovenia.

13. The European Pillar of Social Rights (EPSR) was set out in 2017 at the Gothenburg Summit. The Pillar sets out 20 key principles in three main areas: (1) equal opportunities and access to the labour market (2) fair working conditions and (3) social protection and inclusion.

- The Just Transition Fund (JTF) supports the regions most affected by the transition towards climate neutrality. Through the Just Transition Mechanism, it contributes to the European Green Deal's objective of achieving climate-neutrality in the EU by 2050. The purpose of the JTF is to prevent the exacerbation of regional inequalities resulting from the transition towards climate neutrality, in accordance with the EU's cohesion policy[14].

The governance of Cohesion Policy involves multiple levels of decision-making, including the European Commission, national governments, regional authorities, and other stakeholders. The partnership principle is a key feature of the governance of ESIF. It requires member states to involve relevant public and private stakeholders in the design, implementation, and evaluation of ESIF programmes. This ensures that the funding responds to the needs and priorities of local communities and stakeholders. Member states are required to develop multiannual strategic plans that set out their priorities and objectives for the funding period. These plans must be developed in partnership with relevant stakeholders and approved by the European Commission. Finally, funding is managed through a system of shared management, where member states are responsible for managing and implementing the funding. This means that member states must ensure that the funding is used in accordance with EU rules and regulations, and must report regularly to the European Commission on the progress of their programmes.

Most of the R&I related funding in the new Cohesion Policy 2021-2027 will be oriented towards policy objective 1 (a more competitive and smarter Europe)[15]. Typically, cohesion policy provides funding for R&I activities, including support for collaborative research projects, innovation support for SMEs, innovation networks, capacity building and skills development, technology transfer, as well as funding for the development of innovation infrastructure, such as science parks, incubators, and accelerators, which can help to support innovation activity and attract innovative firms to a region.

There is no overlap – but rather complementarity – across the different eligible initiatives which can be funded by R&I actions under both cohesion policy and Horizon Europe. In turn, this calls for establishing synergies in order to maximize the joint impact of funding and the overall efficiency of the policy framework. Synergies can appear "upstream" and "downstream". The former refers to the case where R&I–related investments under cohesion policy enhance

14. The JTF has dedicated specific objectives indicated in art. 8 of Regulation (EU) 2021/1056 of the EP and of the Council of 24 June 2021 establishing the Just Transition Fund.

15. During the 2014-2020 period, R&I funding was mostly implemented in the context of thematic objectives 1 (strengthening research, technological development and innovation), 2 (enhancing access to, and use and quality of, information and communication technologies) and 3 (enhancing the competitiveness of SMEs).

research infrastructure and equipment and thus create the condition for research actors in a given territory to successfully compete for competitive funding such as Horizon Europe. The latter refers to the development of innovation and /or the successful product commercialization generated from prior R&I-related knowledge. Indeed, this concept can be easily explained by looking at the Technology Readiness Level (TRL) – a common framework for evaluating the maturity of a particular technology[16]. The TRL is typically measured on a scale of 1 to 9, with 1 being the lowest level of maturity and 9 being the highest level of maturity (where R&I funding under cohesion policy tends to be more concentrated). The levels are defined as follows[17]:

1. Basic principles observed
2. Technology concept formulated
3. Experimental proof of concept
4. Technology validated in laboratory
5. Technology validated in relevant environment
6. Technology demonstrated in relevant environment
7. System prototype demonstration in operational environment
8. Actual system completed and qualified
9. Actual system proven in operational environment

2.3. Next Generation EU (NGEU)

The economic impact of the Covid-19 pandemic has been felt by all European Union (EU) member states, with many facing significant challenges in terms of economic recovery. In response, the EU has established the Next Generation EU (NGEU) to support member states in their economic recovery efforts and promoting resilience. One of the key characteristics of NGEU is the significant scale of funding available (around €750 billion) available for investments in a range of areas, such as health, digitalization, climate action, and social cohesion.

The Recovery and Resilience Facility (RRF) is the main instrument of NGEU with a financial envelope of €723.8 billion (in current prices) in loans (€385.8 billion) and grants (€338 billion). The grants are non-repayable funds that are designed to support the recovery effort, while the loans are low-interest loans that aim at supporting investment in key areas. Moreover, both programs include a range of conditions that member states must meet in order to receive funding. These conditions include the development of comprehensive recovery and resilience plans, which must be approved by the European Commission. Finally,

16. The TRL is commonly used by government agencies and public and private organizations to assess the readiness of a technology for practical application.
17. https://ec.europa.eu/research/participants/data/ref/h2020/wp/2014_2015/annexes/h2020-wp1415-annex-g-trl_en.pdf

member states are required to allocate at least 37% of their RRF funding to climate and environmental objectives, and at least 20% of their funding to the digital transition. The reforms and investments proposed by EU Member States in their Recovery and Resilience Plans (RRPs) have exceed these targets for all the countries, as displayed in Figure 1.

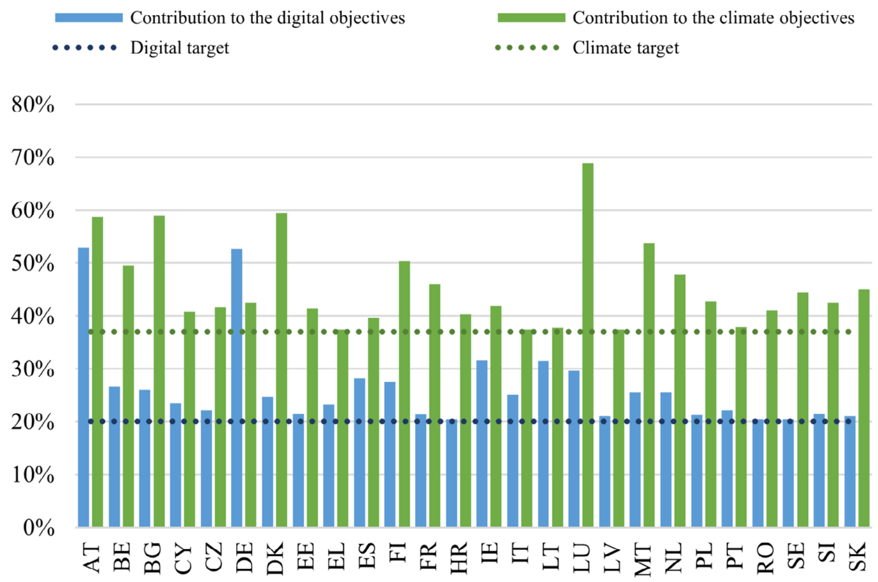
It is worth signalling two important novelties in the implementation of the RRF. First, the extensive role of loans compared to other funding programmes and past programming periods where funding was available (almost) entirely via grants[18] and, especially, the strong linkage in the design of the RRF between funding and reforms that are in line with the EU's priorities and the country-specific recommendations under the European Semester framework of economic and social policy coordination.

The RRF is structured around six pillars:
- Green transition
- Digital transition
- Smart, sustainable and inclusive growth
- Societal and territorial cohesion
- Health, and economic, social and institutional resilience
- Policies for the next generation

Member states are responsible for developing their own recovery and resilience plans, which outline their proposed reforms and investments, and must be approved by the European Commission. The governance of the RRF also includes coordination with national authorities, targeted support for areas that have been particularly affected by the Covid-19 pandemic, and technical assistance provided by the European Commission to member states to support the implementation of the RRF. Compared to the multi-level design of the governance of cohesion policy, the RRF is mostly centralised at the national level with so far light involvement of regional authorities in the monitoring and implementation of the plan[19]. In turn, this constitutes an important issue for both:
- the effective design of place-based policies (for instance on R&I) in terms of governance coordination (when multiple institutional actors are partially involved in different policies)
- the comprehensive impact of policies in terms of synergies between instruments targeting similar priority areas (i.e. "policy objective 1" under the new cohesion policy and the pillar on "societal and territorial cohesion" under the RRF.

18. At the moment, the option of claiming loans is not used by many Member States – for the relative borrowing costs or other considerations – and just Italy, Romania and Greece have claimed the entire eligible amount.
19. https://cor.europa.eu/et/news/Pages/CoR-CEMR-joint-consultation-RRPs.aspx.

Figure 1 – Share of RRPs estimated expenditure towards climate and digital objectives



Source: RRF Scoreboard (data extracted on 28/02/2023)

3. Challenges in Monitoring EU Funds at Regional Level

When multiple funding programs have overlapping objectives and target the same sector or technology, they can compete for the same pool of eligible projects and recipients. This competition can result in reduced funding for individual projects and can limit the potential for collaboration between researchers and organizations. In addition, fragmentation of R&I funding can also lead to misunderstanding and complexity in the application and implementation process. With multiple funding programs and conflicting eligibility criteria, it can be difficult for firms and researchers to navigate the funding landscape and access the resources they need to pursue their research and innovation activities. To maximize the impact of R&I funding programs, it is important to identify and address potential fragmentation, and to actively seek out opportunities for complementarities and synergies between programs. This can be achieved through regular evaluations and assessments of funding programs, and by promoting coordination and collaboration between funding organizations and stakeholders.

To address these challenges, it is important for policy makers to promote coordination and collaboration between funding programs, and to streamline the application and implementation process to reduce complexity and increase access to funding for firms and researchers in lagging regions.

In practical term, a major difficulty comes when managing authorities responsible for the launch of calls for applications of a specific funding programme have no knowledge (or limited information) about the typology of R&I projects other programmes not managed by them support financially. For instance, a clear mapping of the projects funded by different R&I programmes may help local authorities to identify potential synergies (when different instruments are used for achieving the same goal) and potential financial needs (e.g. from R&D to go to market).

The lack of taxonomies across different datasets and multiple observations can be a significant problem in data analysis and interpretation. Taxonomies are classification systems that help organize and categorize data into meaningful groups. Without taxonomies, it can be difficult to compare and combine data from different sources, as the data may not be organized in a consistent or compatible way. This lack of consistency in data organization can lead to several challenges in data analysis, including:

- Data fragmentation: Data may be scattered across multiple sources and may not be integrated into a unified system. In turn, this can make it difficult to identify data patterns or trends across different sources.
- Inconsistencies in data quality: Different sources of data may have varying levels of accuracy, completeness, and consistency. Without a taxonomy to standardize data quality, it can be challenging to determine which sources are most reliable.
- Data duplication: Without a consistent taxonomy, data may be duplicated or recorded in different ways across different datasets, leading to redundancy and inconsistency.
- Challenges in data analysis: Analyzing data without a clear taxonomy can be challenging, as the data may not be organized in a way that is easily comparable or interpretable.
- Inability to make data-driven decisions: Without a consistent taxonomy, it can be difficult to draw meaningful insights from the data and make data-driven decisions.

To address these challenges, it is important to develop standardized taxonomies and classification systems that can be used across different datasets and observations. This can help ensure that data is organized consistently and accurately, making it easier to analyse and interpret. To illustrate such bottlenecks, we use as a practical example of the potential issues policymakers can be faced to identify R&I projects targeted to support a climate-neutral transition. As illustrated in Table 1, existing universal taxonomies to classify EU funded projects

Table 1 – Examples of Existing Taxonomies to Produce Statistics on Environmental or Climate Change-related actions: Description and Potential Limitations

Name	*Description*	*Examples of limitations*
Statistical Classification of Economic Activities in the EU (NACE)	EUROSTAT has developed a methodological approach using NACE classification codes related to recycling, reuse and repair to delimitate circular economy-related economic activities.	This classification does not permit to identify circular economy projects when the development or adoption of more eco-efficient technologies is happening i.e., in manufacturing sector, or developed by ICT actors.
ESI Funds' thematic objectives	During the 2014-2020 period, three ERDF thematic objectives (TO) were directly labelled as green investments: ◦ TO4 – supporting the shift towards a low-carbon economy in all sectors; ◦ TO5 – promoting climate change adaptation, risk prevention and management; ◦ TO6 – preserving and protecting the environment and promoting resource efficiency	Not all green-R&I-related projects may be classified in these categories. If investment projects are classified and financed under the TO1 (strengthening research, technological development and innovation) and TO3 (Enhancing the competitiveness of small and medium-sized enterprises), and then classified in generic intervention fields (e.g. 064 – Research and innovation processes in SMEs), there may not be a direct way to identify green-related projects. Some examples are: (i) the development of a new operating system or software (*innovation process*) able to reduce or avoid products defects; (ii) the development of a biodegradable plastic packaging (*product innovation*); (iii) the development of new materials for building construction (*product innovation*) to improve the insulation of houses and then reduce energy consumption and CO2 emissions.
ESI funds intervention fields' dimension	During the 2014-2020 period, in addition to the more direct dimensions such as "environmental infrastructures" (codes 017-023), "sustainable transport" (codes 043-044) and "environment" (codes 083-095), there are also additional dimensions within other groups associated with low-carbon economy: ◦ 003 (Productive investment in large enterprises linked to the low-carbon economy) ◦ 065 (R&I investments in enterprises focusing on the low carbon economy and on resilience to climate change) ◦ 071 (Development and promotion of enterprises specialised in providing services contributing to the low carbon economy and to resilience to climate change)	

Source: Authors' elaboration

(e.g. NACE codes or ESIF thematic objectives/intervention fields) do not allow having a full picture of the EU funded projects supporting such transition. A potential solution to help to map these activities is using text-mining analysis. This technique refers to the process of extracting knowledge from text documents (Gaikwad *et al*., 2014).

4. Territorial Economic Data Viewer (TEDv)

In order to reinforce the territorial monitoring of different R&I funds, and support policy makers through the provision of novel statistical evidence at regional level, the Joint Research centre of the European Commission launched the Territorial Economic Data viewer (TEDv) in late 2022.

The TEDv is the first available tool which combines statistical territorial information of different EU funding programmes in a single and coherent framework – mainly thanks to the methodological effort on territorial and sectorial/thematic allocations (via taxonomy conversions). Beyond data provided by Eurostat, TEDv includes information from three different R&I funding programmes with different objectives: (i) European Structural and Investment Funds (ESIF) under the thematic objective 1 (TO1 – R&I) for 2014-2020; (ii) Horizon programmes and; (iii) Recovery and Resilience Facility (RRF) under the thematic area R&I. Comprehensive data from ESIF-TO1 and Horizon 2020 (H2020) refer to the programming period 2014-2020 and include the EU contribution of the decided/selected projects or operations. Data for the period 2021-2027 – corresponding to the new policy design of both Cohesion policy and Horizon Europe – are added over time in line with the evolution of the current spending programmes. Finally, RRF data comprises the estimated costs with R&I-related expenditures in the period 2021-2026.

TEDv uses essentially six main source of data:

- EUROSTAT (macro-level data) for socio-economic and demographic indicators, as well as, Research & Development (R&D) statistics.
- COHESION OPEN DATA PLATFORM (macro-level data) to estimate the cumulative amount under the ESIF-TO1 of EU funding share of total eligible costs decided until the last year available (at the date of the present chapter, 2021). Both in the case of Eurostat and this set of data, a NUTS converter (Batista e Silva *et al*., 2020) is used to allow that the statistical information (time series) to be reported in the 2021 NUTS version;
- Horizon Dashboard / eCORDA – COmmon Research DAta Warehouse (micro-level data) to extract the total H2020 funding allocated to each region in the programming period 2014-2020 and the evidence available over time on the ongoing Horizon Europe programme.

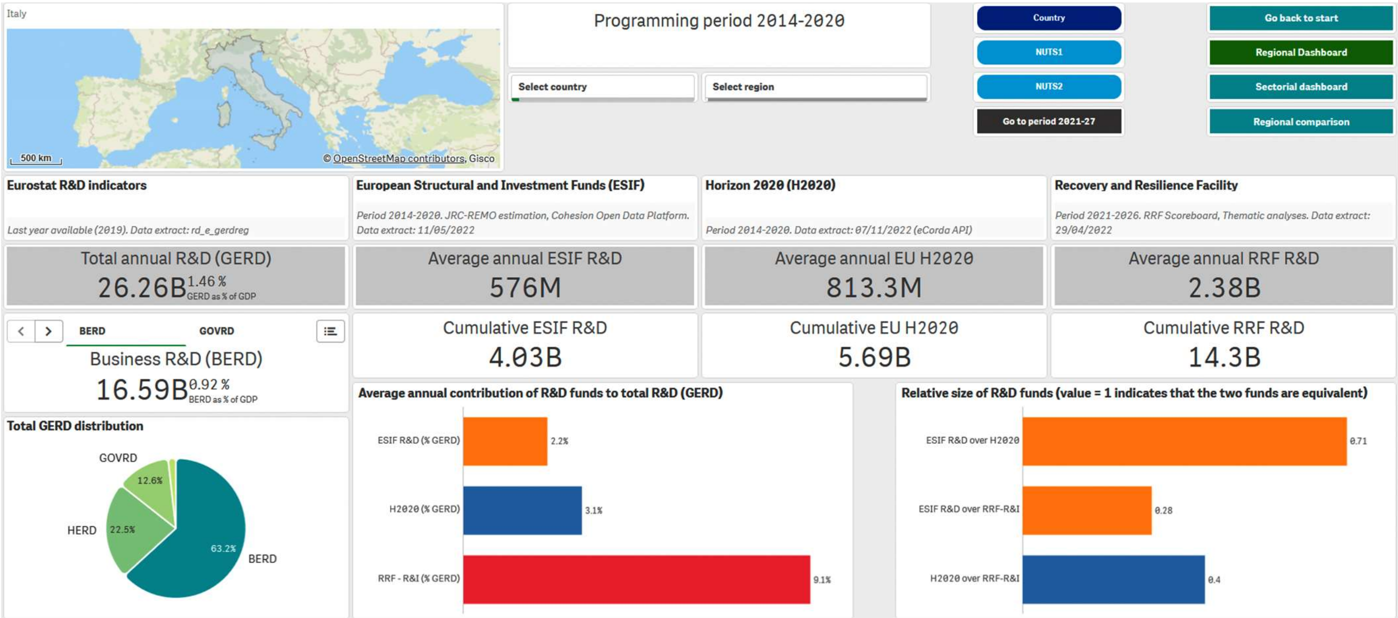
- Recovery and Resilience Scoreboard (macro-level data) to extract the cost estimated for R&I expenditures;
- JRC-WIFO (micro-level) database (Bachtrögler *et al*., 2021) for generating sector-specific statistics (NACE Rev. 2) based on beneficiary-level data on ESIF-TO1;
- BvD ORBIS (micro-level data) to fill gaps concerning the economic activity of the ERDF beneficiaries in the JRC-WIFO database.

Figure 2, Figure 3 and Figure 4 show some examples of TEDv visualisations for Italy and its Nuts 2 administrative regions. For instance, Figure 2 shows the relative importance of the three EU funding programmes with respect to national R&I system and investments (in the case of the RRF, it should be kept in mind that Italy has opted also for the loan component). Figure 3 indicates the sectorial concentration of the different R&I funds and to compare them with the sectorial concentration of the total R&D expenditure in a given territory. Finally, the territorial distribution of EU funds, expressed in per capita terms, is reported in Figure 4. This type of evidence can help in providing ad-hoc support to policy makers in different regions and to illustrate territorial heterogeneity and the way in which place-based policies interact with the local R&I system.

4.1. An Application to Low-carbon ERDF-related Projects: Comparing Result of ESIF Taxonomy vs Text-mining

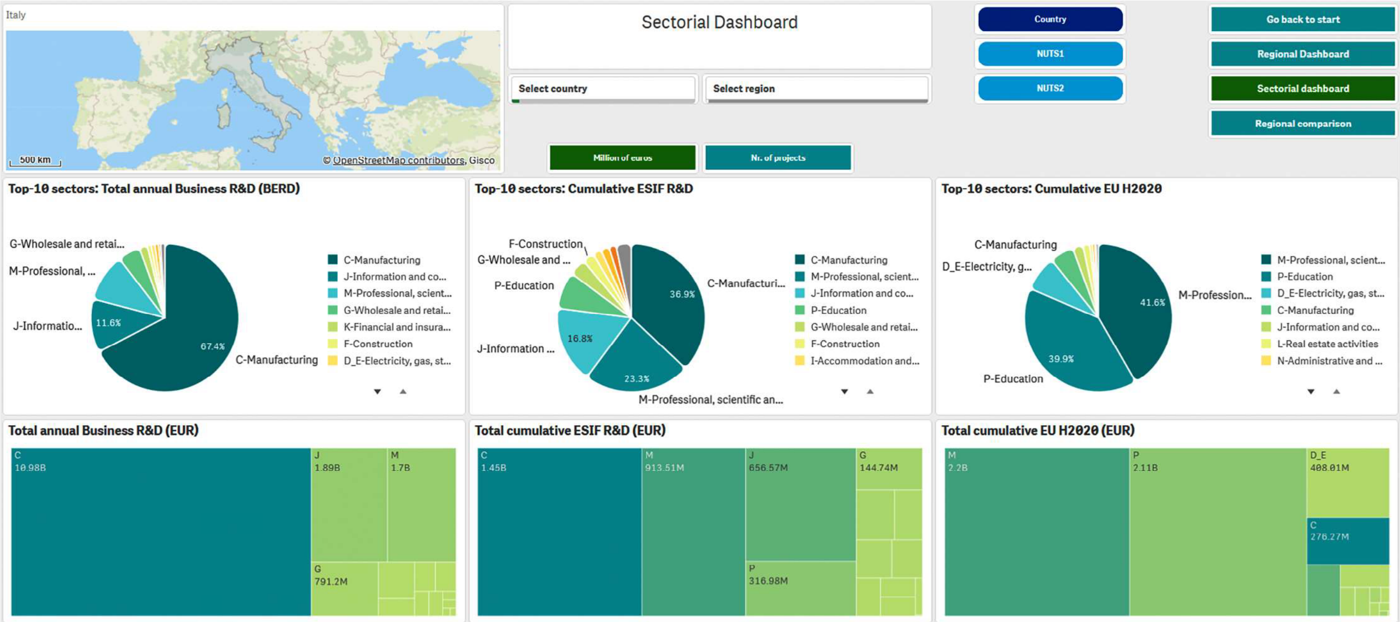
To illustrate the use of TEDv for monitoring thematic R&I projects, we use the results of text-mining analysis performed by Marques Santos *et al*. (2022) to identify ERDF low-carbon technologies-related projects and available in the "Thematic dashboard" of TEDv. To conduct this analysis, Marques Santos *et al*. (2022) used the JRC-WIFO ERDF database (Bachtrögler *et al*., 2021). This database comprises around 600,000 observations on ERDF project beneficiaries during the 2014-2020 period providing a unique coverage and level of details on the ERDF operations. Based on a list of keywords provided by external experts and the European Commission's Directorate General Research and Innovation, several text algorithm runs are made on the text of the projects descriptions to identify those subsets of investments related to low-carbon technologies. Ex-post quality checks are then made on the resulting sample via an iterative process to refine the final list of keywords. ERDF categories of intervention associated to each projects are used to distinguish between R&I and non-R&I projects. Table 2 reports the results of the analysis performed to identify low-carbon industrial technologies-related projects using the JRC-WIFO ERDF database (Bachtrögler *et al*., 2021) and two different techniques: (i) the ESIF intervention fields code associated with "low-carbon economy" (003, 065 and 071) – reported in Table 1; and (ii) text-mining analysis using a list of keywords associated with the concept of "low-carbon industrial technologies" and classified R&I-related projects.

Figure 2 – Example of TEDv Visualisation: Italy Territorial Snapshot



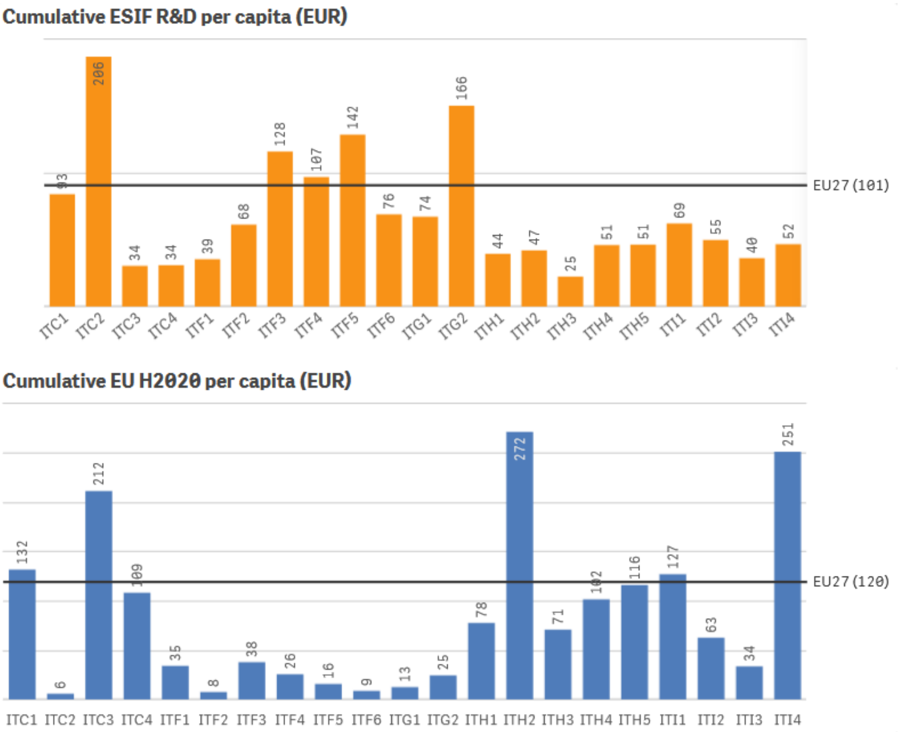
Source: Territorial Economic Data viewer (extracted on 03/03/2023)

Figure 3 – Example of TEDv Visualisation: Italy Sectorial Concentration of ESIF and H2020 Funds Versus Concentration of Total R&D Expenditures



Source: Territorial Economic Data viewer (extracted on 03/03/2023)

Figure 4 – Example of TEDv visualisation: Regional comparison of Italian's regions, ESIF per capita versus H2020 per capita



Source: Territorial Economic Data viewer (extracted on 03/03/2023)

Results tend to differ according to the method and taxonomy used for the analysis. For instance, the use of ESIF taxonomy only leads to the identification of a total amount of R&I EU funds related to "low-carbon economy" equivalent to €1,144 million using the ESIF taxonomy (codes 003, 065 or 071) during the programming period 2014-2020. On the contrary, text-mining analysis – unconstrained by standard taxonomy – leads to the identification of an amount of €3,872 million.[20] In this case, we found that the results of the text-mining analysis technique provide a more comprehensive understanding of the purpose for which the funds are used compared to the existing taxonomy.

20. This value is different from the one reported by Marques Santos *et al*. (2022) because UK is not included in the present analysis.

Table 2 – Low-carbon Industrial Technologies-related Projects, EU27 (ERDF, 2014-2020): ESIF Taxonomy Versus Text-mining Analysis (ml euros)

Category	*EU Funds (MEUR)*	*% Tot ERDF*
ESIF Taxonomy – Intervention Fields		
003 – Productive investment to low-carbon economy	€ 142	0.08%
065 – R&I investment to low-carbon economy	€ 951	0.52%
071 – Business services to low-carbon economy	€ 52	0.03%
Projects classified at least in one of the codes above	€ 1,144	0.63%
Text-mining analysis		
Total R&I low-carbon-related projects	€ 3,872	2.10%

Note: Intervention field codes correspond to 003 (Productive investment in large enterprises linked to low-carbon economy); 065 (Research and innovation infrastructure, processes, technology transfer & cooperation in enterprises focusing on low carbon economy and on resilience to climate change); 071 (Development and promotion of enterprises specialised in providing services contributing to low carbon economy and to resilience to climate change – including support to such services). Since a project can have more than one taxonomy, the sum of the values for the categories 003, 065 and 071 is different from the value for projects classified at least in one of the codes 003, 065 and 071.

Source: Authors' elaboration based on Bachtrögler *et al*. (2021) and Marques Santos *et al.* (2022).

4.2. Territorial mapping of R&I Low-carbon-related Projects Funded by ERDF

Using the results of text-mining analysis, we have estimated a measure of EU funds spatial concentration in R&I low-carbon-related projects, following Billings and Johnson (2012) and their so-called Location Quotient Index (*LQI*). Equation (1) defines *LQI*:

$$LQI_{i,j} = \frac{X_{i,LC} / \sum X_i}{X_{BM,LC} / \sum X_{BM}} \qquad [1]$$

where:

- $LQI_{i,j}$ refers to the location quotient for region *i* regarding the R&I funding to low-carbon-related projects (*LC*);
- $X_{i,LC}$ is equal to the total R&I funding allocated to low-carbon-related projects (*LC*) in region *i*;
- ΣX_i comprises the total of R&I funding allocated to region *i*;
- $X_{BM,LC}$ corresponds to the total of R&I funding in all EU regions (or in the country of region *i*) allocated to low-carbon-related projects (*LC*);
- ΣX_{BM} comprises the total of R&I funding allocated in all EU regions (or in the country of region *i*).

Region i comprises the 240 NUTS-2 level regions of the EU27. Following Doussineau and Bachtrögler-Unger (2021), we consider the existence of EU funds concentration in region i and area j if the $LQI_{i,j}$ is greater than one. A value higher than one means that the region i is concentrating more funds in the investment to support a "low-carbon economy" than the EU (or country) average.

Figure 5 shows the territorial concentration of the R&I funding associated to projects in the area of low-carbon industrial technologies estimated using equation (1), and using the EU average as benchmark. Regions shown in green have an *LQI* value higher than one, while those in pink have a value lower than one. The territorial mapping displays heterogeneous concentration patterns. For example, all regions in Finland, Ireland, the Netherland and Luxembourg, as well as most regions in Poland, Belgium, and Greece, report a value higher than one. On the other hand, territories with values of the index lower than one include Bulgaria, Estonia, Croatia, Hungary, Latvia, Malta, Sweden and Slovenia, as well as most regions in Portugal, Spain, Italy and Austria. On average, more-developed regions show a higher concentration index and a higher likelihood of having R&I funding concentrated in low-carbon economy-related projects compared to less developed or transitions regions (Table 3).

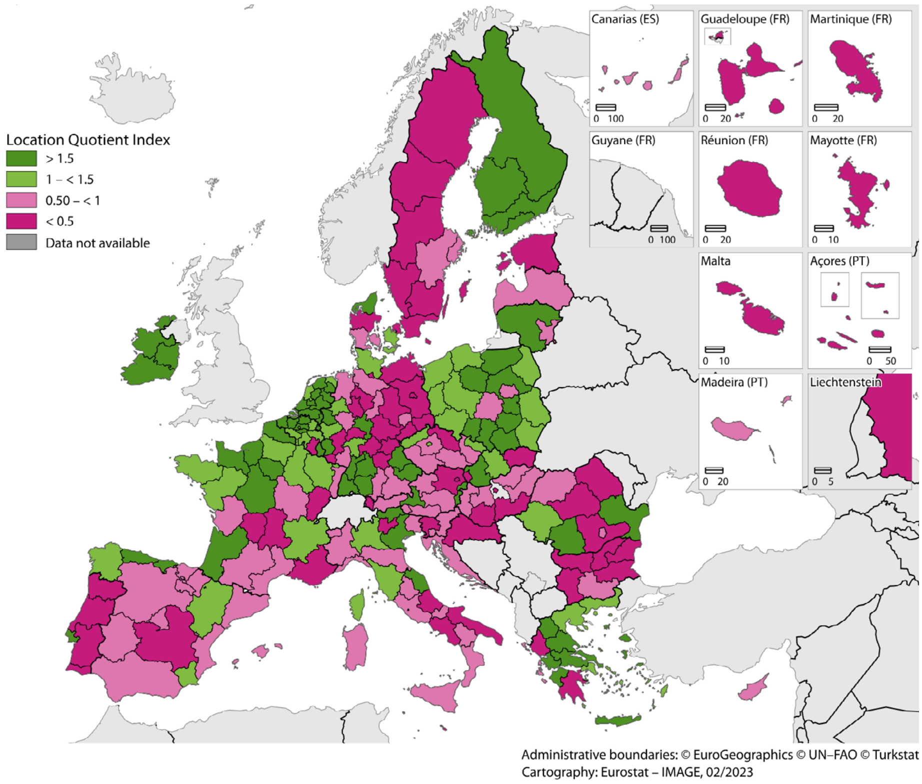
Figure 6 displays the territorial concentration of R&I funding in low-carbon-related projects using the within-country average as benchmark. This figure shows different concentration patterns, although on average, more-developed regions still have a higher *LQI* and a higher likelihood of registering a concentration of EU funds (as shown in Table 4).

Figure 7 combines information from Figure 5 and Figure 6 and, displays the regions by four categories: 1) below the EU and country average (yellow regions); 2) below the EU average but above the country average (orange regions); 3) above the EU average but below the country average (blue regions); 4) above the EU and country average (red regions). Table 5 reports the number of regions in each of these categories. For instance, around 30 EU regions are performing better than the country average but lower than the EU average. Around 65% of the regions with a concentration index below the EU and country average are more developed regions.

4.3. Identifying Complementarities with other R&I Funding

To understand whether there is a relationship with other R&I funding programmes targeted at a carbon-neutral economy, namely the European Commission's Framework programme (FP7) 2007-2013 or Horizon 2020 (H2020) for the period 2014-2020, we performed several t-test for equality of means regarding the funding concentration between regions with an *LQI* higher than one and those below it. Results reported in Table 6 do not show substantial differences

Figure 5 – Location Quotient Index (benchmark EU average): R&I funding to low-carbon industrial technologies, EU27 (ERDF, 2014-2020)



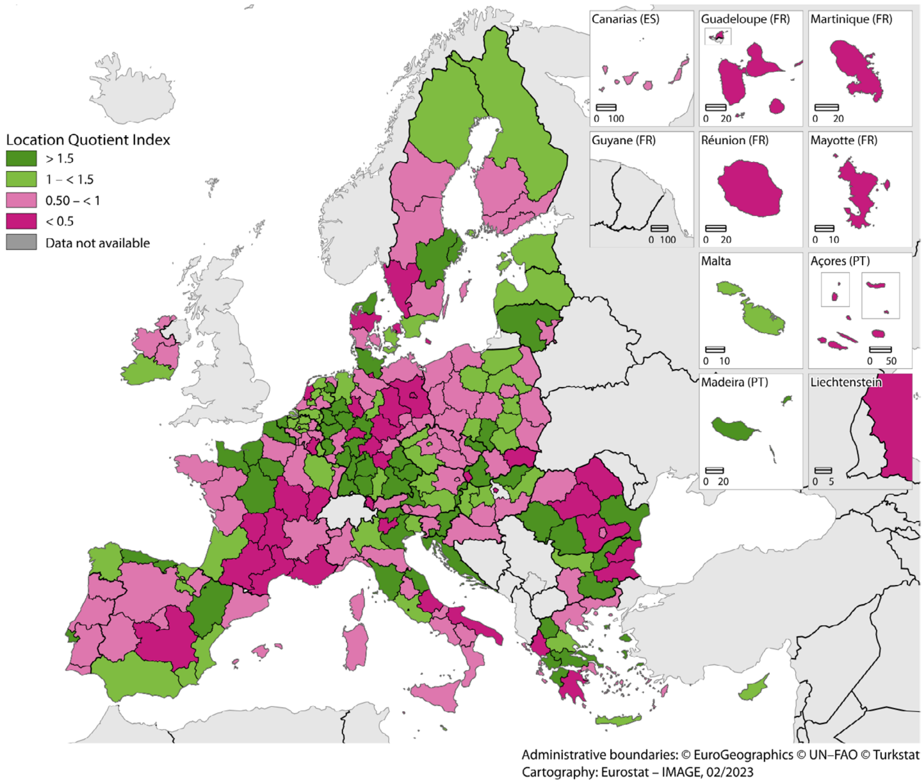
Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021)

Table 3 – Location Quotient Index (benchmark EU average) by Region Category

Category	*LQI (average)*	*LQI>1*	
		Yes	*No*
Cohesion criteria classification (2014-2020)			
Less-developed regions	0.87	0.37	0.63
More-developed regions	1.39	0.50	0.50
Transition regions	0.95	0.36	0.64

Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021)

Figure 6 – Location Quotient Index (benchmark country average): R&I funding to low-carbon industrial technologies, EU27 (ERDF, 2014-2020)



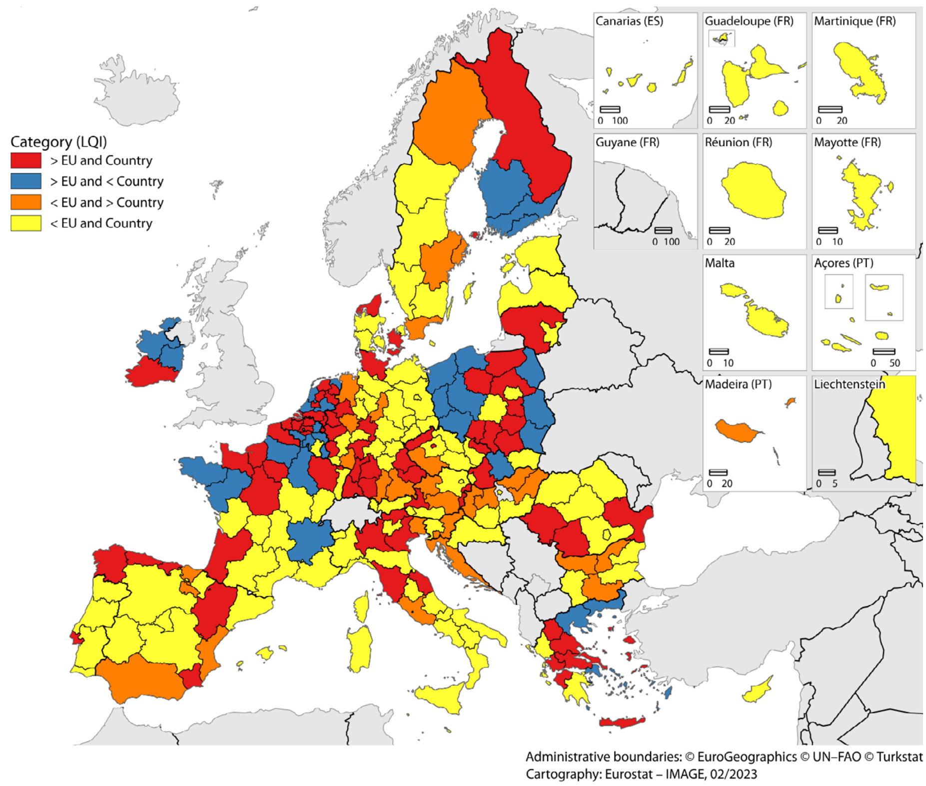
Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021)

Table 4 – Location Quotient Index (benchmark country average) by Region Category

Category	*LQI (average)*	*LQI>1*	
		Yes	*No*
Cohesion criteria classification (2014-2020)			
Less-developed regions	0.96	0.36	0.64
More-developed regions	1.35	0.51	0.49
Transition regions	0.87	0.28	0.72

Source: based on data from Bachtrögler *et al*. (2021)

Figure 7 – Position of Regions with a LQI above (below) the EU and/or Country average: R&I Funding to Low-carbon Industrial Technologies, EU27 (ERDF, 2014-2020)



Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021)

Table 5 – Nr. of Regions with a LQI Above (below) the EU and/or Country Average, by Region Category

Category	*< EU and Country*	*< EU and > Country*	*> EU and < Country*	*> EU and Country*	*Total*
Less developed regions	34	10	11	15	70
More developed regions	45	19	18	47	129
Transition regions	24	1	4	10	39
Total	103	30	33	72	238

Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021)

Table 6 – T-test Equality of Means FP7 / H2020 Environment-related Funding by Group of Regions (concentration of ERDF R&I funding in low-carbon related projects)

	Variables	*Nr. Obs.*		*Mean*		*Diff (Yes-No)*	*St Err*	*P-value*
		Yes	*No*	*Yes*	*No*			
All regions category	FP7 environment per capita	100	130	3.35	2.60	0.75	0.67	0.263
	H2020 environment per capita	105	133	5.86	4.76	1.09	1.04	0.295
	LQI FP7 environment	105	128	1.46	1.45	0.02	0.28	0.947
	LQI H2020 environment	105	130	1.23	1.42	-0.19	0.20	0.343
	LQI FP7 environment > 1 (Y/N)	105	128	0.48	0.42	0.05	0.07	0.409
	LQI H2020 environment > 1 (Y/N)	105	130	0.44	0.52	-0.08	0.07	0.240
Less-developed regions	FP7 environment per capita	22	42	0.56	0.67	-0.11	0.22	0.628
	H2020 environment per capita	26	44	1.07	1.92	-0.85	0.59	0.159
	LQI FP7 environment	26	42	1.04	1.97	-0.93	0.64	0.150
	LQI H2020 environment	26	43	1.06	2.03	-0.98	0.52	0.067
	LQI FP7 environment > 1 (Y/N)	26	42	0.39	0.52	-0.14	0.13	0.271
	LQI H2020 environment > 1 (Y/N)	26	43	0.35	0.65	-0.31	0.12	0.013
More-developed regions	FP7 environment per capita	64	63	4.61	4.48	0.13	1.09	0.907
	H2020 environment per capita	65	64	8.35	7.75	0.60	1.71	0.728
	LQI FP7 environment	65	62	1.50	1.15	0.35	0.32	0.276
	LQI H2020 environment	65	63	1.33	1.03	0.30	0.21	0.167
	LQI FP7 environment > 1 (Y/N)	65	62	0.52	0.36	0.17	0.09	0.057
	LQI H2020 environment > 1 (Y/N)	65	63	0.48	0.43	0.05	0.09	0.586
Transition regions	FP7 environment per capita	14	25	1.98	1.12	0.85	0.80	0.290
	H2020 environment per capita	14	25	3.15	2.12	1.03	1.08	0.349
	LQI FP7 environment	14	24	2.09	1.29	0.79	0.77	0.307
	LQI H2020 environment	14	24	1.11	1.37	-0.25	0.35	0.479
	LQI FP7 environment > 1 (Y/N)	14	24	0.43	0.42	0.01	0.17	0.945
	LQI H2020 environment > 1 (Y/N)	14	24	0.43	0.50	-0.07	0.17	0.680

Note: "Group Yes" includes all the regions with a *LQI* higher than one, using as benchmark the EU average.

Source: Authors' elaborations based on data from Bachtrögler *et al*. (2021) and Horizon dashboard between both groups, except in the subsample composed of less-developed regions or more-developed regions. For instance, in less-developed regions, territories with a concentration of ERDF R&I funding in low-carbon-related projects have a lower concentration of H2020 environment-related projects.

5. Conclusion

Policy monitoring is a key element in the policy cycle. It helps to understand regional patterns and the evaluation / design of more effective policies. This chapter presented a comprehensive overview of European Union (EU) funding programs with a focus on the territorial allocation of R&I funding. It shows how complex could be for policymakers to have a complete picture of the use of funds in their territories. The chapter highlighted several methodological challenges, including the lack of uniform data coverage and multiple taxonomies. To address these issues, the chapter introduced a new tool, the Territorial Economic Data viewer, developed by the European Commission. The TEDv is a pioneering tool that integrates statistical territorial data from various EU funding programs into a unified and consistent framework. As a result, the TEDv enables comparison of the scale of diverse EU funding sources with respect to overall R&D expenditure. This statistical information is especially valuable for policymakers, as it facilitates benchmarking of a region's relative position against national/EU averages and other EU regions. Finally, this chapter provided practical examples of the tool's usefulness in policy support, particularly in the context of mapping low-carbon technologies for the EU's green deal initiative.

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Mappatura territoriale dei finanziamenti dell'UE per le attività di ricerca e innovazione

Sommario

Questo capitolo offre una panoramica completa dei programmi di finanziamento dell'Unione Europea (UE) concentrandosi sulle sfide che i decisori politici affrontano riguardo all'allocazione territoriale e alla mappatura dei fondi UE destinati alle attività di ricerca e innovazione (R&I). Il capitolo illustra diversi aspetti di natura metodologica – ad esempio, la presenza di molteplici tassonomie e la mancanza di copertura uniforme dei dati – che rendono difficile una completa mappatura territoriale dei fondi destinati alla R&I. Per affrontare queste problematiche metodologiche, il capitolo introduce un nuovo strumento sviluppato dalla Commissione Europea – il Territorial Economic Data viewer (TEDv) – con lo scopo di superare queste sfide. Infine, questo capitolo fornisce esempi pratici dell'utilità di TEDv come strumento di supporto per il monitoraggio delle politiche, ad esempio per la mappatura delle tecnologie a basso impatto ambientale nel contesto dell'iniziativa dell'Unione Europea sul Green Deal.

Regional Integration in Domestic and International Value Chains: Employment, Occupations and Skills

Tommaso Ferraresi, Leonardo Ghezzi*, Renato Paniccià**

Abstract

In a period of rapid transformations of GVCs' structure imposed also to the fragility they showed during the COVID period, it is more and more important to have tools able to measure the true single regional contribution of GVCs on the local economy. For this reason, in this paper we extend the use of interregional input-output tables for assessing the employment embodied in the regional value chains, in terms of type of occupations and skills. After the estimation of both the degree of the integration of Italian regions in some important value chains and value chain related indices of labor productivity and hourly wages, we design a new dataset containing information about regional and sector skill content in order to characterize each value chain in terms of demand for skills, knowledge and abilities. We finally identify each single regional contribution to the value chains in terms of skills. Our results suggest that regions greatly differ in terms of their economic involvement in the value chains, with Northern regions far more involved in value chains characterized by a higher level of labor productivity and hourly wages, such as exports and investment goods related value chains. Moreover, the heterogeneity across regions within each value chain is resulted significantly high, with a higher share of highly skilled tasks provided by Northern and Centre regions, even in those value chains in which Southern regions appear to be specialized.

1. Introduction

The Italian economy is characterized by deep regional disparities in terms of patterns of development, and so per-capita GDP and household income especially between the Northern and Southern regions. These stylized facts are well studied by economic literature (see, e.g., Daniele, Malanima, 2007). Economic specialization, reflecting different paths of development also display a high degree of heterogeneity, with Northern regions more involved in high tech sectors both in manufacturing and services, and more innovative in the production of new technologies (see, e.g.,

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Capello, Lenzi, 2022). What is less studied, however, is the regional heterogeneity in the involvement in different value chains (see, e.g., Bentivogli *et al*., 2019; Ferraresi *et al*., 2021), due the strong interrelations amongst them (interregional trade) and/or through foreign trade. This is not a marginal aspect. In the period of rapid transformations of GVCs' structure imposed also to the fragility they showed during the COVID period, the possibility to measure the true single regional contribution of GVCs o the local economy is of vital importance.

For this reason, in this paper we extend the use of interregional input-output tables for assessing the employment embodied in the regional value chains, in terms of type of occupations and skills. After the estimation of both the degree of the integration of Italian regions in some important value chains and value chain related indices of labor productivity and hourly wages, we design a new dataset containing information about regional and sector skill content in order to characterize each value chain in terms of demand for skills, knowledge and abilities. We finally identify each single regional contribution to the value chains in terms of skills. Our results suggest that regions greatly differ in terms of their economic involvement in the value chains, with Northern regions far more involved in value chains characterized by a higher level of labor productivity and hourly wages, such as exports and investment goods related value chains. Moreover, the heterogeneity across regions within each value chain is resulted significantly high, with a higher share of highly skilled tasks provided by Northern and Centre regions, even in those value chains in which Southern regions appear to be specialized.

The use of inter-regional Input-output Tables has recently been applied in the economic literature to evaluate regional integration in global and domestic value chains. Popularized by applications to inter-country Input-output Tables (Koopman *et al*., 2014; Borin, Mancini, 2017; Los *et al*., 2016; Timmer *et al*., 2014), such an approach has been extended to inter-regional data, e.g., by Bentivogli *et al*. (2019) and can also be applied to European NUTS2 regions using the EUREGIO Input-Output database constructed by Thissen *et al*. (2018) and Thissen *et al*. (2019). The definition of a value chain which is used in the paper is also evaluated in Ferraresi *et al*. (2021) to study the ex-ante exposure of Italian regions to the COVID-19 crisis. Moreover, in that work the authors adopt a skill-task based approach to the study of production steps in each value chain in order to disentangle COVID-19 risk and remote work potential (see also Conte *et al*., 2020). The present work goes beyond the narrow focus of the former one in providing a consistent picture of the embeddedness of Italian regions in different value chains in terms of employment, skills and abilities. This work also borrows from analyses of the composition of the Italian labor force in terms of provided skills. Such an approach has been used, for instance, to assess the occupations more prone to the Fourth Industrial revolutions (e.g., Capello, Lenzi, 2022; Faraoni *et al*., 2019), as well as those in which remote work is more likely to be applied (e.g., Barbieri *et al*., 2020; Dingel, Neiman, 2020; Duranti *et al*., 2020; Boeri *et al*., 2020).

The rest of the paper is organized as follows. In Section 2 we provide a description of the methodology and the data. In Section 3 we discuss the main results of the work. An Appendix at the end of the paper provides complementary tables.

2. Methodology and Data

We define a value chain as the set of production steps, employment and skills activated by a final demand shock. A value chain approach allows to go beyond the analysis of isolated economic sectors by considering that different, but interconnected, sectoral production activities must jointly be activated to satisfy the needs/demand expressed by a community of consumers located in different regions, the investment demand coming from firms, and demand stemming from foreign markets.

Figure 1 graphically depicts what is meant as a value chain the context of this work. Let us take, for instance, consumption value chains. Demand for consumption products may be expressed for satisfying different needs (functions) ranging from nourishment and leisure to health care services, etc. Firms belonging to different sectors and areas produce goods and services to directly meet specific consumer needs (direct activation). At the same time, firms' own production processes require raw materials as well as intermediate goods and services provided by other plants, which do not necessarily belong to the same industry. This gives rise to a second production step. Clearly, the process may be further extended, as firms engaged in the second step also demand intermediate inputs and may activate additional production steps (indirect activation). The value chain associated with a specific consumption need/function is therefore defined by the set of firms (and sectors) involved in all the production processes originating from it. Moreover, whereas final demand is localized in space, the set of production steps aiming at serving it is potentially geographically dispersed. Note also that each of the activated production may in turn be viewed as a bundle of tasks, executed by firms' employees, with each task being characterized by different degrees of skill, ability and knowledge content.

Starting from such a definition, in an input output framework, a value chain can be defined as the combination of two components: i. a demand shock affecting a specific need/function; ii. the set of production processes which respond to it. Let $Fd_{z,s}$ be an $(MxN)x1$ final demand shock vector[1] affecting region s, and A the matrix of input coefficients obtained by dividing the intermediate input

1. The number of rows (MxN) in an inter-regional framework is equal to the number of regions (M) times the number of sectors (N).

Figure 1 – Graphical Representation of a Value Chain

Source: IRPET

demand of each sector (i) in every region (j) by its total output (Y_{ij}).[2] In terms of production, a value chain can be defined as:

$$Fd_{z,s} + AFd_{z,s} + A\left(A\right)Fd_{z,s} + A\left(A^2\right)Fd_{z,s} + A\left(A^3\right)Fd_{z,s} + \ldots \\ + A\left(A^{n-1}\right)Fd_{z,s} = \left(I - A\right)^{-1} Fd_{z,s} = Y_{z,s} \qquad [1]$$

with $n \rightarrow \infty$. The left-hand side of the equation reports the chain of production steps as power series approximation activated by the final demand shock. First, the shock itself, which is accommodated by a particular industry, or set of industries; then the first round of demand for intermediate inputs required to accommodate the final demand shock; subsequently, the production of intermediate inputs needed to produce the intermediates demanded in the previous round; and so on.

Whereas the equation (1) defines a value chain in terms of production, we can easily derive value added, labor compensation and employment (both in terms of labor units and hours worked) as follows:

$$W_{z,s} = w \cdot \left(I - A\right)^{-1} \cdot Fd_{z,s} \qquad [2]$$

where $W_{z,s}$ is a vector either representing sector/region value added, employment or labor compensation; and w a diagonal matrix with, on its main diagonal either value added coefficients; labor compensation coefficients; or employment

2. Letting T be the matrix representing the flows of intermediate inputs and Y a diagonal matrix containing the output of each sector in every region on its main diagonal, the input coefficient matrix A is obtained by post-multiplying T by the inverse of Y, i.e., $A=TY^{-1}$.

per unit of output. Data in order to retrieve value added associated to each value chain are drawn from the interregional input-output table estimated by IRPET.[3]

A graphical representation of an interregional input-output table is reported in Figure 2. The interregional input output table (IRIOT) contains information for 43 sectors and 21 Italian regions (including extra-regio). Each row of the matrix indicates the destination of the production generated by a sector j-nth located in r region s distinguishing:

a. the s sectors (indicated in the column headings of the table), distinguished also by region, s purchasing the good/service produced by "j" for their intermediate uses;
b. the final users (distinguished by final demand type and geographical area);
c. foreign exports as an exogenous component.

Focusing on the part relating to intermediate flows, reading IRIOT by column, provides the requirement in terms of intermediate product and productive factors services of each single sector. Evidently, in IRIOT, the origin of the intermediate inputs is distinguished by sector and geographical area of origin. The total of each single column of the intermediate part of IRIOT is the sectoral total output which is made up by demand for intermediate inputs (read per column) and productive factors services (wages and profits) that is value added at basic prices, net indirect taxes.

The accounting structure of the table can be summarized by the following identity, for each j-th sector and r-th region:

$$\sum_{s=1}^{N}\sum_{i=1}^{M} x_{ij}^{sr} + y_j^r + tax_j^r + imports_j^r \equiv \sum_{s=1}^{N}\sum_{i=1}^{M} x_{ji}^{rs} + \sum_{s=1}^{N} fd_j^{rs} + exports_j^s \qquad [3]$$

Where: N= number of regions; M= number of sectors; x = intermediate goods and services; y = value added at basic prices; fd = final demand; tax = indirect taxes; *imports* = intermediate inputs imports; *exports* = international exports.

Referring to Paniccià and Rosignoli (2018) for the datset utilized for estimating IRIOT, about additional data on employment and labor compensation they have been retrieved from Istat regional accounts.

In the analysis we assess 15 different value chains. In particular, we consider 12 consumption-related value chains activated by households' expenditures: 1) food and non-alcoholic beverages; 2) alcoholic beverages, tobacco and narcotics; 3) clothing and footwear; 4) housing, water, electricity, gas and other fuels; 5) furnishings, household equipment and routine household maintenance; 6) health; 7) transport; 8) communication; 9) recreation and culture; 10) education; 11) restaurants and hotels; 12) miscellaneous goods and services. We then consider investment by distinguishing construction investment from other

3. See Paniccià and Rosignoli (2018) for the methodology use for estimated those tables and Bentivogli *et al.* (2019) in order to review the the IRIO model specification.

Figure 2 – A Graphical Representation of the IRPET Interregional Input Output Table (IRIOT)

Source: IRPET

investment (i.e., equipment, R&D, software; henceforth ERDS). Finally, we consider a value chain activated by international exports.

Once estimated the employment embodied in each value chain we distinguish employees by occupations, skills, abilities and knowledge. Given the number of employees activated in each sector and region by a specific value chain we distribute them among the different occupations (at the 1-digit level) according to the shares of each of them resulting from the ISTAT Labor Force Survey (LFS). Each occupation is then linked to the set of skills, abilities and knowledge emerging from the INAPP ICP database. For any 5-digit occupation, the database returns a set of characteristics, in the form of scores (ranging from 0 to 100). Occupation-based indices are obtained at the 4-digit level and then linked to employment at the sectoral/regional scale through the ISTAT Labor Force Survey. Skills are divided in basic and cross-functional skills. Basic skills are developed capacities that facilitate learning or the more rapid acquisition of knowledge. Examples of such skills are writing, mathematics and science. Cross-functional skills are developed capacities that facilitate performance of activities that occur across jobs. Examples are represented by complex problem solving, persuasion, programming. Abilities are enduring attributes of the individual that influence performance. Amongst them we find cognitive abilities (e.g., deductive reasoning, problem sensitivity), physical abilities (e.g., stamina, static strength), psychomotor abilities (e.g., control precision, manual dexterity) and sensory abilities (e.g., auditory attention, depth perception). Finally, knowledge consists of organized sets of principles and facts applying in general domains. They range from mathematics and science to manufacturing and production to business and management.

We link the INAPP ICP database to the LFS and then use the employment composition of each sector and region in terms of occupations in order to compute sector/region scores for skills, abilities and knowledge.

We then compute indices relating skills, abilities and knowledge at the value chain level by weighting the skill index obtained at the region/sector level by the share of its contribution to the total employment activated by such specific value chain. For helping the results' visualization, we normalize those indices on specific skills on a 0 to 1 scale (0 the value chain displaying the minimum value; 1 the value chain displaying the highest value). Finally, in order to assess the specific contribution of each region to any given value chain, we compute specialization indices. That is, we compute ratios between the contributions of a given region to a particular value chain skill and the contributions of the same region to employment in that specific value chain. Values above 1 would then mean that a region is providing a contribution in terms of such peculiar skill which outweigh the one in terms of total employment.

3. Results

Italian regions strongly differ in terms of their integration in value chains. As reported by Table A2 in the Appendix, Northern regions are highly dependent on foreign exports and equipment investment, whereas Southern regions do more rely upon consumption related value chains (in particular, food and beverages) as well as on public administration expenditures related value chains (not investigated in this work).

Different economic specializations entail differentials in terms of labor productivity and hourly wages. As it can be seen from Table 1, productivity is particularly in high in value chains related to communications expenditures (8) and ERDS investment (13), followed by foreign exports (15), transport (7) and recreation and culture related value chains (9).[4] The examined value chains characterized by the lowest productivity levels are instead the one activated by hotels and restaurants expenditures

4. The high values in the housing related expenditures value chains are due to imputed rents.

Table 1 – Labor Productivity and Hourly Wages Computed at the Value Chain Level

	Labor productivity	*Hourly wages*
(1) Food and non-alcoholic beverages	0,0165	0,0198
(2) Alcoholic beverages, tobacco and narcotics	0,0165	0,0198
(3) Clothing and footwear	0,0153	0,0176
(4) Housing, water, electricity, gas and other fuels	0,1090	0,0239
(5) Furnishings, household equipment and routine household maintenance	0,0109	0,0139
(6) Health	0,0156	0,0218
(7) Transport	0,0195	0,0223
(8) Communication	0,0240	0,0250
(9) Recreation and culture	0,0193	0,0237
(10) Education	0,0068	0,0339
(11) Restaurants and hotels	0,0141	0,0178
(12) Miscellaneous goods and services	0,0159	0,0195
(13) ERDS investment	0,0224	0,0237
(14) Construction investment	0,0151	0,0206
(15) Exports	0,0196	0,0242

Notes: Productivity: millions euros per thousands of hours; Hourly wages: millions euros per thousands of hours.

Source Elaborations on Istat data and IRPET IRIOREG 2018

(11) and by furnishing, household equipment and household maintenance related expenditures (5). Differentials in terms of productivity are partly reflected in hourly wages. The highest salaries are paid in the value chain activated by education expenditures (10), communication expenditures (8), foreign export (15), housing (4), ERDS investment (13) and recreation and culture expenditures (9).

Apart from inter-value chains differences, within-value chain interregional heterogeneity stands both in terms of productivity levels and hourly wages (Tables A3 and A4 in the Appendix), with Northern regions being generally more productive and paying higher hourly wages independently of the examined value chain. However, focusing on the Southern regions, productivity levels and hourly wages strongly vary depending on the value chain, suggesting that "progressing" towards more productive value chains would entail a productivity enhancing process for the latter ones.

Value chains also differ in terms of type of occupational shares, with some of them demanding higher shares of high-skill occupations (Table 2), in particular:

education (10), communication (8), recreation and culture (9) and health (6) among consumption expenditures, as well as ERDS investment (13) and foreign export related value chains (15). Whereas the share of low skilled employees is activated by furnishing and personal services (5) as well as by clothes (3) and food (1) and beverages (2) value chains.

Tables from A5 to A8 in the Appendix investigate regional differences in terms of skill content of occupations for 4 specific value chains: food and hotels and restaurants among consumption expenditures related value chains; ERDS investment and foreign export among the others. Again, se have found strong within-value chain cross-regional heterogeneity stands, with Southern regions displaying lower shares of high skilled occupations and higher shares of low skilled occupations in most value chains, even in those generally characterized by higher shares of high skilled occupations.

Table 2 – Shares of Employees by Skill Content of Occupations in the Different Value Chains

	High	*Medium*	*Low*
(1) Food and non-alcoholic beverages	19%	61%	20%
(2) Alcoholic beverages, tobacco and narcotics	19%	61%	20%
(3) Clothing and footwear	17%	62%	21%
(4) Housing, water, electricity, gas and other fuels	28%	54%	17%
(5) Furnishings, household equipment and routine household maintenance	13%	54%	33%
(6) Health	35%	52%	13%
(7) Transport	24%	62%	14%
(8) Communication	50%	42%	9%
(9) Recreation and culture	36%	51%	12%
(10) Education	77%	12%	11%
(11) Restaurants and hotels	11%	74%	15%
(12) Miscellaneous goods and services	26%	48%	26%
(13) ERDS investment	33%	54%	13%
(14) Construction investment	19%	71%	10%
(15) Exports	28%	59%	13%

Notes: High-skill occupations: Managers, Professionals, technicians and associate professionals; Medium-skill occupations: Clerical support workers, Service and sales workers, Skilled agricultural, forestry and fishery workers, Craft and related trades workers, Plant and machines operators and assemblers; Low-skill occupations: Elementary occupations.

Source: Elaborations on Istat data and IRPET IRIOREG 2018

We now move to looking at the results in terms of skills, abilities and knowledge required by different value chains. As it can be seen from Table 3, value chains greatly differ in terms of demanded skills. Most of consumption related value chains do not require high levels of skills, especially when it comes to basic skills and complex cross-functional skills such as complex problem solving, technology design and programming. However, relevant exceptions are represented by education, communication and transports related value chains. A high level of skills is also demanded within ERDS investment related value chain as well as in the foreign exports related one.

Most value chains require technical skills naturally connected with manufacturing tasks as those implied by operation monitoring, operation control, equipment maintenance, troubleshooting and repairing. But when it comes to more cognitive (and social) skills such as complex problem solving, coordination and persuasion, we see that, apart from education and communication value chains only ERDS investment and foreign exports related value chains display high levels of skills. Also, technical skills such as mathematics, operational analysis, technology design and programming display disproportionately higher values in these value chains with respect to other ones.

Tables A9 and A10 in the Appendix complement information from Table 3 by providing indices about abilities and knowledge at the value chain level. In terms of abilities (Table A9), it is interesting to observe that the education value chains mostly dominate those requiring abstract reasoning whereas construction investment related value chain is the one prevailing when it comes to psychomotor, physical and sentitive abilities. The latter abilities are present in all the value chains requiring manufacturing stages. Value chains requiring complex manufacturing activities also complement high indices in such abilities with high values in indices linked to cognitive abilities. This is especially the case of ERDS investment value chains and exports-related value chains. When it comes to knowledge (Table A10) it is interesting to first observe the coherence between the different fields and the scores displayed by the different value chains. For instance, food preparation displays the higher values in the value chains activated by hotels and restaurants expenditures, food expenditures and alcoholic beverages consumption. The value chain activated by health expenditures instead is the one with the highest value in the indices for medicine and dentistry as well as for therapy and counseling. Knowledge in communication and media and in telecommunication is higher in the communication value chain and that in transports in the transport value chain. Value chains linked to manufacturing activities are also those displaying the highest values in indices related to economics and business accounting, administration and management, production and processing. Finally, indices for computers and electronics, design and engineering and technology display higher values in value chains activated by communication expenditures, ERDS investment and exports.

From the general assessment of skills, abilities and knowledge, we can see how ERDS investment-related value chains and exports related value chains tend to emerge as those demanding the most diversified set of items: from basic to cross-functional skills; from cognitive to physical abilities; from theoretical to more "practical" kind of knowledge. Among consumption related value chains, communication expenditures activate higher order skills, abilities and types of knowledge.

We finally explore the interrelations among economic specialization in particular value chains, that about specific skills and geographical areas. More precisely, we consider whether providing specific skills to a value chain at the regional level is positively correlated to the fact that the region is particularly embedded in such value chain, controlling for the geographical area to which each region belongs (North, Centre, South). We thus collect data from economic specializations (indices containing the ratios between regional contribution to a value chain and the regional contribution to employment in the economy) as well as indices of skill participation to each value chains (the ratio between the share of regional contribution in terms of a specific skill to a value chain and its contribution in terms of employment). We then run regressions in which regional indices of the skills evaluated at the value chain/regional levels are functions of economic specializations of each region in each value chain and geographical areas fixed effects.

Results are reported in Table 4. First, Southern regions do display significantly lower levels of skill content in most areas. With respect to the baseline outcome (Northern regions) coefficients for Southern area is most of time negative and significant. This is noticeable for complex and technical skills such as complex problems solving, programming, mathematics and science. Very few are the exceptions and generally linked to blue collar manufacturing activities such as operation monitoring, equipment maintenance and repairing. Also, Centre regions do display lower demand for high level skills with respect to Northern regions as well as higher level skill demand with respect to Southern regions. As to the relations between economic and skill content specializations, these are most of times not significant. When statistically significant, the coefficients tend to be positive for skills tightly linked to manufacturing tasks such as quality control analysis, system analysis, troubleshooting and equipment selection. Economic specialization seems to reinforce especially those kinds of skills which are more linked to industrial activities, whereas more complex skills, linked to higher level tasks seem to be unrelated to economic specializations in terms of value chains but are probably connected to the presence of high-tech sectors providing high level tasks to all value chains in some regional economies.

Table 3 – Skills Indices by Value Chain at the National level (minimum 0 – maximum 1)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Basic skills: content															
Reading Comprehension	0,23	0,22	0,16	0,54	0,00	0,45	0,42	0,79	0,54	1,00	0,15	0,32	0,57	0,36	0,51
Active Listening	0,08	0,09	0,12	0,34	0,00	0,40	0,25	0,64	0,42	1,00	0,03	0,30	0,40	0,22	0,30
Writing	0,21	0,21	0,16	0,48	0,00	0,44	0,37	0,71	0,49	1,00	0,10	0,29	0,51	0,28	0,44
Speaking	0,21	0,21	0,17	0,39	0,00	0,42	0,32	0,57	0,45	1,00	0,12	0,26	0,41	0,20	0,33
Mathematics	0,54	0,54	0,36	0,64	0,00	0,33	0,59	0,96	0,63	1,00	0,27	0,25	*0,78*	*0,84*	*0,79*
Science	*0,22*	*0,22*	*0,09*	*0,34*	*0,00*	*0,41*	*0,21*	*0,58*	*0,36*	*1,00*	*0,03*	*0,19*	*0,40*	*0,38*	*0,39*
Basic skills: process															
Critical Thinking	0,16	0,15	0,12	0,42	0,00	0,38	0,28	0,70	0,45	1,00	0,08	0,28	0,46	0,29	0,44
Active Learning	0,15	0,14	0,11	0,42	0,00	0,40	0,25	0,73	0,46	1,00	0,03	0,29	0,47	0,36	0,46
Learning Strategies	0,07	0,07	0,05	0,20	0,00	0,23	0,12	0,36	0,26	1,00	0,08	0,15	0,23	0,16	0,21
Monitoring	0,22	0,21	0,13	0,43	0,00	0,34	0,28	0,60	0,44	1,00	0,30	0,23	0,45	0,39	0,49
Cross-functional skills: social															
Social Perceptiveness	*0,12*	*0,12*	*0,20*	*0,27*	*0,24*	*0,46*	*0,22*	*0,35*	*0,35*	*1,00*	*0,17*	*0,40*	0,27	0,00	0,20
Coordination	0,27	0,26	0,20	0,56	0,00	0,52	0,41	0,67	0,54	1,00	0,37	0,29	0,54	0,60	0,54
Persuasion	0,20	0,20	0,21	0,39	0,15	0,42	0,30	0,59	0,46	1,00	0,00	0,40	0,40	0,15	0,29
Negotiation	0,32	0,32	0,20	0,49	0,00	0,45	0,35	0,78	0,54	1,00	0,04	0,37	0,53	0,23	0,43
Instructing	0,18	0,18	0,13	0,28	0,00	0,30	0,21	0,45	0,35	1,00	0,26	0,16	0,34	0,26	0,33
Service Orientation	0,17	0,18	0,30	0,37	0,30	0,55	0,31	0,67	0,50	1,00	0,41	0,52	*0,43*	*0,00*	*0,29*
Cross-functional skills: complex problem solving															
Complex Problem Solving	0,11	0,10	0,11	0,48	0,08	0,42	0,22	0,80	0,46	1,00	0,00	0,37	0,51	0,43	0,49
Cross-functional skills: technical															
Operations Analysis	*0,32*	*0,30*	*0,19*	*0,54*	*0,00*	*0,44*	*0,32*	*0,99*	*0,58*	*1,00*	*0,10*	*0,27*	*0,69*	*0,65*	*0,72*

(continue...)

(...continue...)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Technology Design	0,25	0,24	0,18	0,40	0,07	0,26	0,29	1,00	0,48	0,70	0,00	0,13	0,64	0,58	0,64
Equipment Selection	0,09	0,06	0,01	0,30	0,00	0,26	0,05	0,77	0,34	1,00	0,17	0,09	0,49	0,75	0,60
Installation	0,34	0,32	0,14	0,47	0,00	0,16	0,33	1,00	0,46	0,17	0,14	0,03	0,64	0,97	0,65
Programming	0,10	0,10	0,09	0,18	0,05	0,07	0,16	1,00	0,34	0,22	0,00	0,09	0,43	0,18	0,30
Quality Control Analysis	0,54	0,53	0,33	0,44	0,00	0,35	0,41	1,00	0,55	0,20	0,63	0,05	0,74	0,60	0,84
Operation Monitoring	0,81	0,78	0,51	0,71	0,29	0,62	0,69	0,63	0,56	0,00	0,79	0,28	0,74	0,96	1,00
Operation and Control	0,75	0,72	0,48	0,72	0,29	0,60	0,67	0,83	0,61	0,00	0,67	0,30	0,81	0,98	1,00
Equipment Maintenance	0,75	0,73	0,43	0,64	0,22	0,39	0,61	0,62	0,51	0,00	0,63	0,17	0,68	1,00	0,83
Troubleshooting	0,63	0,61	0,42	0,68	0,24	0,37	0,62	0,99	0,60	0,00	0,57	0,24	*0,78*	*1,00*	*0,87*
Repairing	*0,73*	*0,71*	*0,37*	*0,61*	*0,15*	*0,22*	*0,57*	*0,73*	*0,48*	*0,00*	*0,30*	*0,06*	*0,69*	*1,00*	*0,85*
Cross-functional skills: systems															
Systems Analysis	0,48	0,46	0,22	0,54	0,00	0,32	0,42	1,00	0,55	0,26	0,20	0,08	0,73	0,61	0,81
Systems Evaluation	0,44	0,43	0,24	0,51	0,00	0,36	0,43	1,00	0,55	0,25	0,21	0,10	0,70	0,54	0,74
Judgment and Decision Making	0,52	0,51	0,26	0,62	0,00	0,31	0,47	1,00	0,63	0,40	0,27	0,26	0,71	0,58	0,67
Cross-functional skills: resource management															
Time Management	*0,09*	*0,08*	*0,11*	*0,36*	*0,00*	*0,27*	*0,21*	*0,79*	0,43	1,00	0,02	0,28	0,46	0,29	0,42
Management of Financial Resources	0,69	0,67	0,35	0,65	0,03	0,23	0,53	1,00	0,67	0,00	0,28	0,28	0,76	0,62	0,69
Management of Material Resources	0,86	0,84	0,40	0,61	0,05	0,41	0,61	0,69	0,63	0,65	0,65	0,00	0,79	0,99	1,00
Management of Personnel Resources	0,57	0,55	0,34	0,78	0,00	0,50	0,60	0,97	0,79	1,00	0,70	0,31	0,82	0,70	0,83

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): ERDS investment; (14): Construction investment; (15): Exports.

Source: Elaborations on Istat and INAPP data and IRPET IRIOREG 2018

Table 4 – Relations between Skills Specialization Indices and Employment Specialization in Value Chains Controlling for Areas

		Area (Base = North)	
	Specialization	*Centre*	*South*
Basic skills: content			
Reading Comprehension	-0,02	**-0,02**	**-0,07**
Active Listening	-0,00	**-0,01**	**-0,03**
Writing	-0,02	**-0,02**	**-0,08**
Speaking	**-0,01**	**-0,01**	**-0,04**
Mathematics	-0,01	**-0,03**	**-0,10**
Science	0,01	**-0,05**	**-0,12**
Basic skills: process			
Critical Thinking	0,00	**-0,02**	**-0,07**
Active Learning	0,00	**-0,02**	**-0,07**
Learning Strategies	0,00	**-0,02**	**-0,08**
Monitoring	0,01	**-0,02**	**-0,07**
Cross-functional skills: social			
Social Perceptiveness	**-0,02**	**-0,01**	**-0,04**
Coordination	0,00	**-0,02**	**-0,05**
Persuasion	**-0,02**	**-0,02**	**-0,06**
Negotiation	-0,01	**-0,02**	**-0,05**
Instructing	0,00	**-0,03**	**-0,06**
Service Orientation	-0,01	**-0,01**	**-0,04**
Cross-functional skills: complex problem solving			
Complex Problem Solving	**0,02**	**-0,02**	**-0,07**
Cross-functional skills: technical			
Operations Analysis	**0,03**	**-0,03**	**-0,08**
Technology Design	0,02	**-0,04**	**-0,11**
Equipment Selection	**0,04**	-0,01	**-0,04**
Installation	0,02	**-0,06**	**-0,06**
Programming	-0,01	**-0,09**	**-0,28**
Quality Control Analysis	**0,05**	-0,02	**-0,06**
Operation Monitoring	0,00	-0,02	**0,04**
Operation and Control	0,02	**-0,02**	0,00
Equipment Maintenance	0,01	-0,02	**0,06**
Troubleshooting	**0,03**	**-0,02**	**-0,02**
Repairing	0,00	**-0,03**	**0,07**
Cross-functional skills: systems			
Systems Analysis	**0,05**	**-0,03**	**-0,06**
Systems Evaluation	0,03	**-0,03**	**-0,08**
Judgment and Decision Making	0,00	**-0,02**	**-0,08**
Cross-functional skills: resource management			
Time Management	0,00	**-0,01**	**-0,04**
Management of Financial Resources	-0,02	-0,02	**-0,10**
Management of Material Resources	0,01	0,00	0,00
Management of Personnel Resources	-0,01	**-0,03**	**-0,11**

Note: Coefficients significant at 10% in bold

Source: Elaborations on Istat and INAPP data and IRPET IRIOREG 2018

4. In Lieu of a Conclusion

In this work we have documented regional involvement in different value chains terms of employment, productivity, wages, occupations and skills using a novel dataset in which interregional input output data are complemented with information about employment, labor cost, occupations and skills.

Our results suggest that value chains differ in terms of labor productivity, hourly wages and demanded skills, abilities and knowledge. Value chains activated by communication expenditures, non-construction investment and exports tend to be more productive, pay higher wages and, consistently, demand higher and more complex skills, abilities and knowledge. Moreover, Italian regions greatly differ in terms of their economic specializations, with Northern regions far more involved in value chains characterized by a higher level of labor productivity and hourly wages, such as exports and investment related value chains. Finally, the heterogeneity across regions within each value chain is high, with a higher share of highly skilled tasks provided by Northern and Centre regions, even in those value chains in which Southern regions appear to be specialized.

Our analysis could be extended over several dimensions. First, we could extend the regression analysis so as to explore the correlations between productivity, hourly wages and skills over the different value chains. Second, we could use the dichotomy sector vs. value chain specialization in order to identify which kind of skills tend to cluster at the value chain level and which are instead those which tend to provide general purpose abilities across all value chain groups. Finally, we could relate skills and abilities at the regional level with those connected via (both backward and forward) inter-sector linkages to see whether activating (backward) more complex skills and/or being activated (forward) by more complex skills is positively correlated by the complexity of skills developed locally.

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Integrazione regionale nelle catene del valore nazionali e internazionali: Occupazione, professioni e competenze

Sommario

In un periodo di rapide trasformazioni della struttura delle catene globali del valore (GVC), imposte anche dalla fragilità che hanno mostrato durante il periodo COVID, è sempre più importante disporre di strumenti in grado di misurare il contributo regionale delle filiere produttive all'economia locale. Per questo motivo, in questo lavoro estendiamo *l'uso delle tavole input-output interregionali per valutare l'occupazione incorporata nelle catene del valore regionali, in termini di tipologia di occupazioni e competenze. Dopo la stima sia del grado di integrazione delle regioni italiane in alcune importanti catene del valore sia degli indici relativi a produttività e retribuzione oraria relativi alla catena del valore, costruiamo un nuovo set di dati contenente informazioni sul contenuto delle competenze regionali e settoriali al fine di caratterizzare ciascuna catena del valore in termini di domanda di competenze, conoscenze e capacità. Identifichiamo infine ogni singolo contributo regionale alle catene del valore in termini di competenze. I nostri risultati suggeriscono che le regioni differiscono notevolmente in termini di coinvolgimento economico nelle catene del valore, con le regioni settentrionali molto più coinvolte nelle catene del valore caratterizzate da un livello più elevato di produttività del lavoro e salari orari, come le esportazioni e le catene del valore relative ai beni di investimento. Inoltre, l'eterogeneità tra regioni all'interno di ciascuna catena del valore è molto elevata, con una quota maggiore di mansioni altamente qualificate fornite dalle regioni del Nord e del Centro, anche in quelle catene del valore in cui le regioni meridionali sembrano essere specializzate.*

Appendix

Table A1 – Labels for Italian NUTS 2 Regions

Area	*Label*	*Description*
North	pie	Piedmont
	vda	Aosta Valley
	lom	Lombardy
	taa	Trentino Sudtirol
	ven	Veneto
	fvg	Friuli Venezia Giulia
	lig	Liguria
	ero	Emilia-Romagna
Centre	tos	Tuscany
	umb	Umbria
	mar	Marche
	laz	Lazio
South	abr	Abruzzo
	mol	Molise
	cam	Campania
	pug	Apulia
	bas	Basilicata
	cal	Calabria
	sic	Sicily
	sar	Sardinia

Table A2 – Employment Specializations of Italian Regions in Different Value Chains

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*PA*
pie	4%	1%	2%	3%	5%	2%	5%	1%	2%	1%	6%	7%	8%	5%	24%	22%
vda	5%	1%	2%	4%	6%	2%	4%	0%	2%	1%	10%	5%	5%	6%	12%	34%
lom	4%	1%	2%	3%	5%	2%	4%	1%	2%	1%	7%	8%	7%	6%	28%	18%
taa	5%	1%	2%	3%	5%	2%	3%	0%	2%	1%	12%	5%	6%	8%	17%	28%
ven	5%	1%	3%	3%	5%	2%	4%	1%	2%	1%	7%	6%	7%	6%	28%	20%
fvg	4%	1%	2%	3%	6%	3%	3%	0%	2%	1%	6%	8%	6%	5%	24%	27%
lig	4%	1%	3%	4%	6%	2%	5%	1%	2%	1%	7%	8%	6%	6%	18%	26%
ero	5%	2%	2%	3%	5%	2%	4%	1%	2%	1%	7%	6%	7%	5%	27%	20%
tos	4%	1%	3%	3%	5%	2%	4%	1%	2%	1%	8%	7%	6%	5%	23%	24%
umb	5%	2%	3%	3%	6%	2%	4%	1%	3%	1%	6%	8%	6%	6%	17%	26%
mar	5%	1%	5%	3%	5%	2%	4%	1%	3%	1%	6%	7%	7%	5%	21%	25%
laz	4%	1%	3%	4%	7%	2%	4%	1%	3%	1%	7%	7%	7%	6%	14%	29%
abr	6%	2%	4%	4%	5%	2%	4%	0%	2%	1%	5%	6%	5%	9%	18%	27%
mol	7%	2%	3%	4%	7%	2%	4%	1%	2%	2%	4%	6%	5%	9%	11%	32%
cam	7%	2%	4%	4%	7%	2%	5%	1%	2%	1%	5%	6%	5%	7%	12%	31%
pug	8%	2%	4%	4%	4%	2%	4%	1%	2%	1%	8%	6%	5%	7%	11%	31%
bas	8%	2%	3%	4%	5%	2%	4%	0%	2%	1%	6%	5%	5%	8%	16%	30%
cal	9%	3%	3%	4%	6%	2%	4%	0%	2%	1%	6%	7%	3%	6%	6%	36%
sic	7%	2%	3%	4%	6%	2%	4%	1%	2%	1%	7%	7%	4%	5%	8%	36%
sar	6%	2%	3%	4%	8%	2%	4%	1%	3%	1%	8%	7%	4%	6%	8%	34%

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): ERDS investment; (14): Construction investment; (15): Exports

Source: Elaborations on Istat data and IRPET IRIOREG 2018

Table A3 – Labor Productivity of Italian Regions in Different Value Chains

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
pie	0,018	0,018	0,016	0,118	0,011	0,015	0,020	0,025	0,020	0,006	0,013	0,016	0,022	0,016	0,019
vda	0,014	0,014	0,017	0,141	0,013	0,016	0,025	0,022	0,018	0,009	0,015	0,018	0,025	0,017	0,022
lom	0,022	0,022	0,018	0,121	0,012	0,018	0,022	0,027	0,023	0,007	0,016	0,021	0,025	0,017	0,022
taa	0,020	0,020	0,019	0,135	0,014	0,016	0,023	0,023	0,021	0,008	0,019	0,023	0,026	0,018	0,023
ven	0,018	0,018	0,017	0,114	0,012	0,016	0,019	0,022	0,019	0,006	0,014	0,016	0,021	0,016	0,019
fvg	0,016	0,016	0,015	0,117	0,011	0,014	0,019	0,023	0,018	0,006	0,014	0,018	0,021	0,016	0,019
lig	0,019	0,019	0,016	0,136	0,011	0,016	0,021	0,024	0,019	0,008	0,015	0,015	0,023	0,014	0,021
ero	0,019	0,019	0,017	0,120	0,012	0,016	0,020	0,023	0,019	0,007	0,015	0,016	0,022	0,017	0,021
tos	0,018	0,018	0,016	0,116	0,011	0,016	0,021	0,023	0,019	0,008	0,015	0,015	0,023	0,015	0,019
umb	0,016	0,016	0,016	0,097	0,011	0,014	0,018	0,018	0,016	0,007	0,013	0,013	0,019	0,014	0,017
mar	0,015	0,016	0,015	0,103	0,013	0,015	0,018	0,020	0,017	0,007	0,013	0,014	0,019	0,014	0,016
laz	0,019	0,019	0,016	0,109	0,009	0,017	0,021	0,028	0,023	0,008	0,014	0,015	0,025	0,016	0,021
abr	0,014	0,014	0,014	0,095	0,011	0,015	0,017	0,020	0,017	0,006	0,013	0,014	0,020	0,011	0,016
mol	0,013	0,012	0,013	0,088	0,011	0,014	0,016	0,018	0,016	0,006	0,011	0,013	0,020	0,013	0,014
cam	0,015	0,015	0,013	0,091	0,009	0,014	0,016	0,021	0,016	0,006	0,013	0,013	0,019	0,013	0,015
pug	0,011	0,011	0,013	0,081	0,010	0,013	0,015	0,018	0,015	0,006	0,011	0,013	0,017	0,012	0,012
bas	0,013	0,013	0,015	0,090	0,011	0,015	0,022	0,018	0,016	0,006	0,012	0,013	0,024	0,014	0,023
cal	0,009	0,009	0,013	0,079	0,010	0,014	0,018	0,020	0,015	0,005	0,010	0,012	0,021	0,012	0,012
sic	0,012	0,012	0,013	0,102	0,009	0,013	0,016	0,024	0,015	0,005	0,012	0,012	0,020	0,013	0,013
sar	0,013	0,013	0,012	0,084	0,008	0,013	0,016	0,021	0,015	0,005	0,013	0,010	0,021	0,012	0,016

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): ERDS investment; (14): Construction investment; (15): Exports; Productivity: millions euros per thousands of hours.

Source: Elaborations on Istat data and IRPET IRIOREG 2018

Table A4 – Hourly Wages of Italian Regions in Different Value Chains

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
pie	0,023	0,023	0,019	0,025	0,014	0,022	0,025	0,026	0,026	0,035	0,019	0,021	0,025	0,022	0,025
vda	0,019	0,019	0,019	0,026	0,015	0,024	0,023	0,025	0,025	0,027	0,018	0,021	0,023	0,022	0,024
lom	0,026	0,026	0,022	0,027	0,017	0,025	0,026	0,029	0,028	0,034	0,020	0,023	0,027	0,024	0,027
taa	0,023	0,023	0,022	0,027	0,018	0,025	0,025	0,025	0,025	0,029	0,022	0,023	0,025	0,025	0,025
ven	0,022	0,022	0,019	0,024	0,015	0,022	0,023	0,024	0,024	0,032	0,018	0,019	0,023	0,021	0,023
fvg	0,021	0,022	0,018	0,025	0,014	0,022	0,023	0,024	0,024	0,033	0,018	0,023	0,024	0,022	0,025
lig	0,021	0,021	0,018	0,024	0,015	0,022	0,022	0,026	0,025	0,034	0,018	0,019	0,026	0,021	0,025
ero	0,023	0,023	0,020	0,025	0,016	0,023	0,023	0,025	0,024	0,033	0,019	0,021	0,025	0,023	0,026
tos	0,021	0,021	0,018	0,024	0,014	0,022	0,023	0,023	0,022	0,034	0,018	0,018	0,023	0,021	0,022
umb	0,020	0,020	0,017	0,022	0,014	0,021	0,020	0,020	0,021	0,035	0,017	0,017	0,020	0,020	0,021
mar	0,019	0,020	0,017	0,022	0,015	0,021	0,021	0,023	0,021	0,035	0,016	0,018	0,021	0,020	0,021
laz	0,021	0,021	0,017	0,026	0,013	0,022	0,023	0,028	0,025	0,033	0,018	0,020	0,025	0,021	0,025
abr	0,018	0,018	0,016	0,022	0,013	0,020	0,021	0,022	0,021	0,036	0,015	0,017	0,021	0,018	0,022
mol	0,015	0,015	0,014	0,022	0,012	0,020	0,020	0,019	0,021	0,037	0,014	0,017	0,020	0,018	0,021
cam	0,015	0,015	0,014	0,020	0,011	0,018	0,018	0,020	0,019	0,035	0,014	0,015	0,018	0,016	0,018
pug	0,014	0,014	0,014	0,020	0,012	0,019	0,018	0,019	0,019	0,036	0,014	0,016	0,018	0,016	0,017
bas	0,015	0,015	0,015	0,021	0,013	0,019	0,019	0,020	0,021	0,037	0,015	0,016	0,019	0,017	0,020
cal	0,012	0,012	0,013	0,019	0,010	0,018	0,017	0,019	0,019	0,036	0,013	0,015	0,017	0,015	0,014
sic	0,014	0,014	0,013	0,022	0,010	0,019	0,019	0,020	0,019	0,036	0,014	0,014	0,018	0,017	0,017
sar	0,016	0,017	0,013	0,022	0,010	0,019	0,019	0,022	0,020	0,036	0,016	0,014	0,019	0,018	0,020

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): ERDS investment; (14): Construction investment; (15): Exports; Hourly wages: millions euros per thousands of hours.

Source: Elaborations on Istat data and IRPET IRIOREG 2018

Table A5 – Occupations Shares of Employees of Italian Regions Embedded in the Food and Non-alcoholic Beverages Value Chain

reg	*high*	*medium*	*low*
pie	24%	63%	13%
vda	15%	69%	15%
lom	26%	60%	14%
taa	19%	64%	16%
ven	22%	65%	13%
fvg	18%	67%	14%
lig	22%	66%	12%
ero	23%	63%	14%
tos	20%	66%	14%
umb	16%	69%	15%
mar	18%	70%	12%
laz	23%	59%	18%
abr	15%	70%	15%
mol	17%	67%	16%
cam	13%	66%	21%
pug	10%	55%	34%
bas	8%	52%	39%
cal	7%	41%	52%
sic	11%	56%	32%
sar	12%	66%	22%

Table A6 – Occupations Shares of Employees of Italian Regions Embedded in the Hotels and Restaurants Value Chain

reg	*high*	*medium*	*low*
pie	11%	78%	11%
vda	7%	80%	13%
lom	14%	72%	14%
taa	9%	76%	15%
ven	10%	79%	11%
fvg	10%	78%	12%
lig	11%	77%	12%
ero	13%	74%	13%
tos	9%	76%	14%
umb	8%	79%	13%
mar	9%	79%	11%
laz	13%	72%	15%
abr	10%	81%	9%
mol	13%	78%	9%
cam	8%	77%	15%
pug	7%	72%	21%
bas	5%	69%	26%
cal	5%	62%	32%
sic	9%	70%	21%
sar	9%	75%	15%

Notes: High-skill occupations: Managers, Professionals, technicians and associate professionals; Medium-skill occupations: Clerical support workers, Service and sales workers, Skilled agricultural, forestry and fishery workers, Craft and related trades workers, Plant and machines operators and assemblers; Low-skill occupations: Elementary occupations.

Source: Elaborations on Istat data and IRPET IRIOREG 2018

Table A7 – Occupations shares of employees of Italian regions embedded in the ERDS investment value chain

reg	*high*	*medium*	*low*
pie	37%	52%	11%
vda	30%	58%	12%
lom	39%	49%	12%
taa	33%	54%	12%
ven	31%	59%	10%
fvg	31%	56%	12%
lig	33%	56%	11%
ero	35%	54%	12%
tos	30%	56%	13%
umb	25%	62%	13%
mar	27%	62%	10%
laz	39%	47%	14%
abr	26%	61%	12%
mol	28%	61%	10%
cam	25%	60%	14%
pug	22%	65%	13%
bas	18%	62%	20%
cal	21%	56%	22%
sic	24%	58%	17%
sar	20%	63%	16%

Table A8 – Occupations shares of employees of Italian regions embedded in the exports value chain

reg	*high*	*medium*	*Low*
pie	30%	59%	10%
vda	23%	65%	11%
lom	32%	55%	12%
taa	27%	61%	12%
ven	26%	64%	10%
fvg	27%	62%	11%
lig	30%	58%	12%
ero	31%	58%	11%
tos	24%	66%	10%
umb	20%	69%	11%
mar	22%	69%	9%
laz	34%	51%	15%
abr	20%	71%	9%
mol	21%	69%	10%
cam	18%	65%	16%
pug	14%	60%	25%
bas	12%	64%	23%
cal	10%	44%	46%
sic	17%	55%	28%
sar	19%	64%	15%

Notes: High-skill occupations: Managers, Professionals, technicians and associate professionals; Medium-skill occupations: Clerical support workers, Service and sales workers, Skilled agricultural, forestry and fishery workers, Craft and related trades workers, Plant and machines operators and assemblers; Low-skill occupations: Elementary occupations

Source: Elaborations on Istat data and IRPET IRIOREG 2018

Table A9 – Abilities indices by value chain at the National level (minimum 0 – maximum 1)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Cognitive abilities															
Oral Comprehension	0,16	0,16	0,14	0,43	0,00	0,40	0,31	0,67	0,46	1,00	0,14	0,27	0,46	0,32	0,38
Written Comprehension	0,36	0,36	0,24	0,65	0,00	0,50	0,55	0,88	0,63	1,00	0,29	0,33	0,67	0,50	0,64
Oral Expression	0,23	0,23	0,17	0,40	0,00	0,38	0,33	0,61	0,45	1,00	0,21	0,26	0,42	0,27	0,36
Written Expression	0,20	0,20	0,17	0,49	0,00	0,43	0,39	0,72	0,50	1,00	0,11	0,29	0,52	0,25	0,45
Fluency of Ideas	0,12	0,11	0,09	0,22	0,00	0,21	0,10	0,52	0,33	1,00	0,28	0,17	0,32	0,20	0,30
Originality	0,11	0,11	0,11	0,17	0,00	0,14	0,12	0,47	0,31	1,00	0,29	0,07	0,28	0,15	0,24
Problem Sensitivity	0,12	0,11	0,10	0,43	0,00	0,39	0,25	0,74	0,44	1,00	0,19	0,27	0,47	0,36	0,46
Deductive Reasoning	0,12	0,12	0,11	0,42	0,00	0,32	0,25	0,71	0,44	1,00	0,05	0,26	0,45	0,33	0,40
Inductive Reasoning	0,15	0,15	0,17	0,44	0,16	0,39	0,27	0,69	0,45	1,00	0,00	0,38	0,45	0,40	0,41
Information Ordering	0,17	0,16	0,13	0,45	0,00	0,37	0,31	0,75	0,49	1,00	0,15	0,27	0,52	0,28	0,52
Flexibility of Closure	0,20	0,19	0,18	0,29	0,09	0,32	0,23	0,61	0,41	1,00	0,00	0,24	0,41	0,15	0,40
Mathematical Reasoning	0,42	0,41	0,24	0,54	0,00	0,27	0,44	0,88	0,52	1,00	0,16	0,22	0,65	0,69	0,66
Number Facility	0,71	0,72	0,48	0,73	0,00	0,38	0,71	1,00	0,72	0,96	0,44	0,33	0,86	0,80	0,87
Memorization	0,23	0,22	0,18	0,40	0,00	0,30	0,36	0,55	0,43	1,00	0,34	0,24	0,42	0,28	0,43
Speed of Closure	0,21	0,20	0,16	0,55	0,00	0,41	0,42	0,78	0,53	1,00	0,16	0,33	0,55	0,46	0,53
Category Flexibility	0,22	0,21	0,18	0,46	0,00	0,38	0,37	0,72	0,50	1,00	0,04	0,23	0,52	0,52	0,52
Perceptual Speed	0,13	0,11	0,14	0,40	0,00	0,30	0,31	0,51	0,42	1,00	0,19	0,21	0,43	0,36	0,50
Spatial Orientation	0,36	0,33	0,29	0,40	0,44	0,41	0,38	0,00	0,30	1,00	0,39	0,32	0,20	0,65	0,27
Visualization	0,34	0,35	0,32	0,45	0,15	0,18	0,35	0,36	0,42	0,79	0,44	0,00	0,42	1,00	0,54
Selective Attention	0,11	0,09	0,10	0,39	0,00	0,22	0,30	0,67	0,40	1,00	0,00	0,22	0,45	0,37	0,51
Time Sharing	0,02	0,00	0,07	0,35	0,08	0,30	0,23	0,61	0,41	1,00	0,39	0,30	0,37	0,22	0,39

(continue...)

(...continue...)

Table A9 – Abilities indices by value chain at the National level (minimum 0 – maximum 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Psychomotor abilities															
Arm-Hand Steadiness	0,49	0,48	0,58	0,39	0,78	0,61	0,36	0,04	0,30	0,00	0,91	0,54	0,35	1,00	0,53
Manual Dexterity	0,67	0,66	0,62	0,41	0,63	0,59	0,48	0,14	0,38	0,00	1,00	0,43	0,42	0,83	0,57
Finger Dexterity	0,72	0,70	0,64	0,38	0,57	0,65	0,43	0,19	0,39	0,00	1,00	0,36	0,48	0,99	0,68
Control Precision	0,70	0,69	0,60	0,59	0,51	0,56	0,59	0,41	0,48	0,00	0,62	0,39	0,61	1,00	0,82
Multilimb Coordination	0,61	0,59	0,42	0,42	0,44	0,47	0,44	0,00	0,32	0,07	0,87	0,28	0,30	1,00	0,45
Response Orientation	0,51	0,47	0,26	0,42	0,28	0,52	0,42	0,00	0,28	0,05	0,91	0,18	0,29	1,00	0,54
Rate Control	0,54	0,51	0,33	0,44	0,31	0,34	0,41	0,05	0,28	0,00	0,62	0,19	0,32	1,00	0,57
Reaction Time	0,54	0,51	0,29	0,49	0,33	0,54	0,50	0,00	0,30	0,01	0,74	0,24	0,30	1,00	0,55
Wrist-Finger Speed	0,62	0,60	0,49	0,39	0,48	0,48	0,42	0,21	0,37	0,00	1,00	0,35	0,38	0,80	0,51
Speed of Limb Movement	0,59	0,57	0,41	0,34	0,49	0,48	0,39	0,03	0,30	0,00	1,00	0,34	0,26	0,72	0,37
Physical abilities															
Static Strength	0,70	0,69	0,53	0,47	0,59	0,61	0,48	0,14	0,38	0,00	0,62	0,44	0,38	1,00	0,46
Explosive Strength	0,69	0,65	0,36	0,40	0,48	0,31	0,32	0,00	0,30	0,02	0,45	0,29	0,21	1,00	0,32
Dynamic Strength	0,64	0,62	0,43	0,43	0,55	0,45	0,38	0,05	0,33	0,00	0,57	0,37	0,30	1,00	0,41
Trunk Strength	0,62	0,61	0,47	0,39	0,62	0,53	0,39	0,02	0,31	0,00	0,72	0,43	0,28	1,00	0,36
Stamina	0,50	0,48	0,30	0,37	0,46	0,22	0,28	0,00	0,25	0,07	0,61	0,28	0,20	1,00	0,30
Extent Flexibility	0,57	0,55	0,49	0,38	0,70	0,48	0,36	0,00	0,31	0,08	0,84	0,47	0,27	1,00	0,34
Dynamic Flexibility	0,64	0,62	0,45	0,42	0,66	0,48	0,34	0,00	0,32	0,12	0,93	0,46	0,26	1,00	0,35
Gross Body Coordination	0,62	0,60	0,42	0,41	0,53	0,49	0,39	0,00	0,35	0,20	1,00	0,37	0,29	0,98	0,37
Gross Body Equilibrium	0,36	0,34	0,23	0,36	0,35	0,34	0,23	0,00	0,23	0,13	0,53	0,27	0,19	1,00	0,25

(...continue...)

(...continue...)

Table A9 – Abilities indices by value chain at the National level (minimum 0 – maximum 1)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Sensitive abilities															
Near Vision	0,31	0,29	0,44	0,29	0,20	0,39	0,30	0,00	0,26	0,03	0,33	0,05	0,47	1,00	0,84
Far Vision	0,50	0,47	0,34	0,55	0,41	0,44	0,50	0,00	0,36	0,58	0,65	0,29	0,30	1,00	0,45
Visual Color Discrimination	0,69	0,68	0,65	0,30	0,25	0,50	0,43	0,24	0,39	0,31	0,55	0,00	0,42	1,00	0,74
Night Vision	0,65	0,60	0,35	0,76	0,33	0,53	0,78	0,28	0,42	0,00	0,36	0,32	0,38	1,00	0,45
Peripheral Vision	0,47	0,44	0,17	0,53	0,17	0,24	0,50	0,00	0,28	0,41	0,80	0,09	0,20	1,00	0,36
Depth Perception	0,46	0,43	0,18	0,46	0,12	0,27	0,47	0,00	0,26	0,21	0,37	0,05	0,22	1,00	0,36
Glare Sensitivity	0,68	0,63	0,20	0,64	0,07	0,33	0,79	0,18	0,34	0,00	0,18	0,05	0,32	1,00	0,45
Hearing Sensitivity	0,46	0,42	0,21	0,45	0,39	0,50	0,46	0,00	0,29	0,58	0,58	0,27	0,24	1,00	0,49
Auditory Attention	0,46	0,42	0,18	0,43	0,28	0,54	0,48	0,00	0,34	1,00	0,89	0,19	0,24	1,00	0,45
Sound Localization	0,45	0,42	0,24	0,47	0,35	0,55	0,47	0,00	0,32	0,72	0,78	0,26	0,25	1,00	0,44
Speech Recognition	0,12	0,11	0,22	0,16	0,42	0,46	0,19	0,00	0,24	1,00	0,64	0,36	0,09	0,23	0,05
Speech Clarity	0,05	0,04	0,11	0,18	0,06	0,29	0,18	0,33	0,29	1,00	0,14	0,23	0,23	0,00	0,17

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): Non-construction investment; (14): Construction investment; (15): Exports.

Source: Elaborations on Istat and INAPP data and IRPET IRIOREG 2018

Table A10 – Knowledge indices by value chain at the National level (minimum 0 – maximum 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Business and Management															
Administration and Management	0,75	0,74	0,49	0,80	0,18	0,43	0,71	1,00	0,76	0,00	0,48	0,50	0,83	0,56	0,78
Administrative	0,45	0,45	0,32	0,78	0,07	0,44	0,63	1,00	0,71	0,11	0,00	0,46	0,76	0,40	0,63
Economics and Accounting	0,70	0,70	0,49	0,90	0,16	0,38	0,75	1,00	0,76	0,00	0,33	0,69	0,87	0,51	0,76
Sales and Marketing	0,99	1,00	0,75	0,60	0,36	0,53	0,79	0,86	0,78	0,00	0,82	0,47	0,77	0,44	0,68
Customer and Personal services	0,48	0,49	0,67	0,45	0,80	0,81	0,59	0,84	0,70	0,18	1,00	0,89	0,58	0,00	0,33
Personnel and Human Resources	0,60	0,58	0,37	0,81	0,01	0,48	0,64	1,00	0,79	0,00	0,89	0,35	0,85	0,57	0,85
Manufacturing and production															
Production and Processing	0,81	0,79	0,57	0,63	0,23	0,36	0,60	0,68	0,57	0,00	0,79	0,22	0,77	0,83	1,00
Food production	0,72	0,70	0,16	0,08	0,08	0,15	0,14	0,08	0,14	0,01	1,00	0,05	0,10	0,00	0,15
Engineering and Technology															
Computers and Electronics	0,21	0,21	0,17	0,38	0,03	0,23	0,33	1,00	0,48	0,42	0,00	0,16	0,55	0,34	0,44
Engineering and Technology	0,20	0,20	0,13	0,45	0,04	0,12	0,32	1,00	0,43	0,26	0,00	0,08	0,62	0,81	0,59
Design	0,24	0,24	0,24	0,52	0,09	0,11	0,36	1,00	0,49	0,21	0,00	0,08	0,74	0,99	0,78
Building construction	0,06	0,06	0,03	0,30	0,01	0,03	0,09	0,07	0,07	0,02	0,00	0,02	0,10	1,00	0,11
Mechanical	0,59	0,56	0,32	0,58	0,12	0,22	0,58	0,37	0,37	0,00	0,19	0,05	0,65	1,00	0,93
Mathematics and Science															
Mathematics	0,54	0,54	0,36	0,64	0,00	0,33	0,59	0,96	0,63	1,00	0,27	0,25	0,78	0,84	0,79
Physics	0,22	0,22	0,07	0,42	0,00	0,29	0,25	0,36	0,31	1,00	0,09	0,06	0,42	0,80	0,51
Chemistry	0,45	0,44	0,23	0,41	0,37	0,75	0,22	0,00	0,24	1,00	0,47	0,33	0,36	0,84	0,60
Biology	0,36	0,35	0,16	0,08	0,14	0,61	0,14	0,04	0,22	1,00	0,23	0,22	0,12	0,00	0,12
Psychology	0,10	0,10	0,22	0,19	0,35	0,58	0,15	0,22	0,31	1,00	0,26	0,45	0,17	0,00	0,10
Sociology and Anthropology	0,06	0,06	0,15	0,12	0,27	0,40	0,09	0,17	0,25	1,00	0,21	0,35	0,13	0,00	0,09
Geography	0,16	0,16	0,07	0,13	0,00	0,10	0,20	0,14	0,18	1,00	0,07	0,04	0,12	0,05	0,10

(...continue...)

(...continue...)

Table A10 – Knowledge indices by value chain at the National level (minimum 0 – maximum 1)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*
Health services															
Medicine and Dentistry	0,04	0,04	0,14	0,02	0,35	1,00	0,03	0,00	0,17	0,44	0,01	0,49	0,05	0,00	0,02
Therapy and Counseling	0,05	0,05	0,29	0,06	0,65	1,00	0,07	0,05	0,23	0,72	0,05	0,69	0,09	0,00	0,04
Education and Training															
Education and Training	0,02	0,02	0,02	0,08	0,00	0,16	0,05	0,16	0,15	1,00	0,02	0,07	0,10	0,04	0,09
Arts and Humanities															
Italian language	0,06	0,06	0,06	0,22	0,00	0,21	0,19	0,44	0,30	1,00	0,13	0,18	0,27	0,05	0,20
Foreign language	0,15	0,15	0,13	0,36	0,00	0,32	0,38	0,93	0,56	1,00	0,63	0,22	0,52	0,13	0,40
Fine arts	0,00	0,00	0,06	0,03	0,10	0,05	0,02	0,13	0,18	1,00	0,02	0,08	0,07	0,03	0,05
History and Archeology	0,00	0,00	0,01	0,03	0,01	0,02	0,01	0,06	0,11	1,00	0,04	0,02	0,03	0,00	0,01
Philosophy and Teology	0,02	0,02	0,05	0,04	0,11	0,12	0,03	0,11	0,14	1,00	0,06	0,12	0,05	0,00	0,03
Law and Public Safety															
Public safety and Security	0,13	0,13	0,05	0,52	0,00	0,20	0,24	0,10	0,29	1,00	0,12	0,08	0,21	0,56	0,24
Law and Government	0,57	0,57	0,29	1,00	0,00	0,71	0,72	0,86	0,79	0,86	0,19	0,57	0,74	0,71	0,59
Communications															
Telecommunications	0,17	0,17	0,09	0,34	0,00	0,17	0,27	1,00	0,44	0,25	0,08	0,13	0,44	0,27	0,27
Communications and Media	0,11	0,11	0,08	0,33	0,00	0,19	0,22	1,00	0,55	0,90	0,04	0,22	0,43	0,07	0,24
Transportation															
Transports	0,71	0,69	0,32	0,68	0,06	0,31	1,00	0,36	0,39	0,00	0,18	0,04	0,47	0,69	0,59

Notes: (1): Food and non-alcoholic beverages; (2): Alcoholic beverages, tobacco and narcotics; (3): Clothing and footwear; (4): Housing, water, electricity, gas and other fuels; (5): Furnishings, household equipment and routine household maintenance; (6): Health; (7): Transport; (8): Communication; (9): Recreation and culture; (10): Education; (11): Restaurants and hotels; (12): Miscellaneous goods and services; (13): Non-construction investment; (14): Construction investment; (15): Exports.

Source: Elaborations on Istat and INAPP data and IRPET IRIOREG 2018

Poverty Adaptation, Multidimensional Well-Being and Regional Disparities in Italy: A Statistical Matching Approach

Cristina Bernini, Silvia Emili*, Maria Ferrante**

Abstract

The deep transformations affecting nowadays the economies have an impact on individuals' well-being, which represents the foundation for sustainable development and poverty reduction. Well-being is a multidimensional concept and the capacity to measure its different aspects is of crucial importance for designing policies. This chapter delves into a particular aspect and presents an analysis of how people's subjective well-being adapts to poverty by digging deeper into the impact a variation in economic condition has, with respect to the previous year, on overall life satisfaction and several domains of life. To investigate if regional disparities in these relationships exist, the analysis is developed for the whole country and the main macro-areas (North vs Centre-South). To overcome the problem of obtaining information on poverty and subjective well-being, we suggest using a statistical matching approach. Findings show that adaptation is rejected for people entering into poverty at the current time or when a poor person's condition worsens over the last year. Significant regional differences in the SWB-poverty adaptation nexus are detected, especially for economic and health domains. Findings support place-based policies aimed at reducing disparities in the living conditions of the residents.

1. Introduction: A Regional Analysis of Poverty Adaptation

There is a general consensus that well-being represents a basis for sustainable development and poverty reduction, for countries at all stages of development. Poverty and well-being are closely related, being poverty another way of describing well-being failures. In this sense, well-being is a social concept, and the features that enable or not to people to achieve well-being have to be taken into account for the assessment of development and sustainable progress. These aspects are particularly relevant nowadays, because the deep transformations that are affecting the economies have also an impact on individuals' well-being.

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In the last decades, investigation into the determinants of well-being, both at the country and regional level, has in fact become a key topic for national and international policymakers, enriching the research on happiness economics. Analyses on the economic conditions of individuals, proxied by their level of material well-being (MWB), the degree of subjective well-being, evaluated by overall life satisfaction (SWB), and the investigation of the main relationships between MWB and SWB are the focuses of the Economic of Happiness literature (for a recent review, see Clark, 2018). Recently, a part of this research has turned its attention to happiness adaptation (Clark *et al.*, 2016). Whether SWB adapts to poverty is a relevant issue to shed light on how to enact policies aimed at increasing the SWB of individuals in poverty (Luo, 2022; Graham, 2016).

Regarding the MWB – SWB relationships, the reference-dependence theory (Clark *et al.*, 2008; Kahneman, Tversky, 1979; Vendrik, Woltjer, 2007) has reached an overall consensus, sustaining that individuals compare their material conditions, measured by the level of their disposable income, with both the material conditions of other people (i.e. peers) and their own past economic conditions (i.e. adaptation). The idea of evaluating people's living status as a function of relative income is generally consistent with the existence of comparison income terms in the individual well-being function (Clark, 2017). The rationale is that subjective well-being is positively affected by one's own income, but negatively by the income of some reference groups (Clark *et al.*, 2008). As stated by Clark (2018, p. 253), "*Individuals are happier when they earn more, but less happy as others earn more. This is most often suggested to reflect social status, envy or some similar phenomenon.*"

The idea that people adapt to poverty and deprivation by learning to suppress their wants, hopes and aspirations has gained a significant level of interest in the analysis of poor regions (Clark, 2009). Adaptation to income level is also proposed as one of the possible explanations to the well-known Easterlin (1974) paradox, i.e. life satisfaction remains constant within a country despite consistent economic growth (Clark, 2016). The limited studies on adaptation, in general, have depicted the negative effects of poverty on SWB, that continue to have a significant effect for a number of years (Clark *et al.*, 2016; Luo, 2022).

Inspired by the relevant role of poverty adaptation to SWB, this study aims to shed new light on a few issues in the nexus, to the best of our knowledge yet to be investigated, regarding how variations in economic conditions impact the intensity of poverty adaptation on SWB, whether there is a territorial dimension to the relationship between SWB and poverty adaptation, and to provide results supporting the multidimensionality concept of subjective well-being.

First, differently from previous literature, which concentrates on the impact of being in poverty for a number of years (Luo, 2022; Clark *et al.*, 2016), we focus on whether adaptation is affected by the bettering or worsening of economic conditions with respect to the previous year. The rationale is that poor individuals may be impacted differently by a change in their economic condition, adapting to poverty with a different intensity. Then, our first research question is whether poverty adaptation is affected by the intensity of the income change of poor individuals.

Second, several studies have shown that regional and contextual characteristics play a substantial role in the definition of poverty and well-being (Ayala, Jurado 2011; Ballas *et al.*, 2017; Bramley *et al.*, 2000), and the role of territorial characteristics in mediating the impact of poverty on SWB has been well-established in literature (see among others: Lawless, Lucas, 2011; Clark, 2017; Giarda, Moroni, 2018; Welsch, Biermann, 2019; Ferrer-i-Carbonell, 2005). Conversely, not enough attention has been paid to the regional analysis of adaptation, though it is a relevant aspect for a country, such as Italy, marked by a strong regional divide (North vs Centre-South) (Capello, 2016; Patacchini, 2008). Thus, we posit the following research questions: does poverty adaptation vary across territories? To what extent do regional disparities affect the SWB-poverty adaptation relationship?

Finally, the conceptualization of SWB as a multidimensional phenomenon is a commonly accepted idea (Cummins, 1996; van Praag, Ferrer-i-Carbonell, 2004); that is, individuals distinguish between various aspects of life and evaluate them separately in terms of how satisfied they are with respect to each of these domains (Diener, 1984). As for poverty, Rojas (2008) find that income has a greater impact on the satisfaction level of the life domains strongly related to income; while Mysíková *et al.* (2019) suggest that the analysis of satisfaction in respect to perceived economic conditions should include numerous non-economic domains reflecting individuals' perceptions of health, productivity, intimacy, safety, community, and emotional well-being. To push this stream of research ahead, we posit two further questions in this study: are all life domains equally affected by poverty adaptation? Are there any life domains more sensitive to poverty adaptation than others?

To answer to these questions, detailed information about income, SWB and regional characteristics are needed. Due to the complexity of these phenomena, in the last thirty years national and international statistical institutes have developed a number of surveys to provide evidence of the relationship between subjective and material well-being, resulting in a body of datasets that collect information, usually referred to independent samples of statistical units over time and among surveys. Focusing on Italy, information on these aspects is provided by different surveys carried out by the Italian Institute of Official Statistics (ISTAT). Each of the surveys has several interesting and specific aspects, stemming from different sets of pros and cons in the use of a certain survey instead of another to study the poverty-SWB relationship. However, there is not a single survey that allows for an exhaustive analysis of poverty and the SWB of Italian households; the lack of a unique database may be overcome by using a statistical matching approach, allowing us to combine different sources of information and guaranteeing model estimates.

To investigate our research questions, we combine the ISTAT surveys of Aspect of Daily Life (ADL) and the Households Budget (BF) Survey, in 2016. To this aim, in this paper we propose a statistical matching approach to combine information about poverty conditions, life domains and regional characteristics for Italy. The joint information allows us to show the effect of adaptation to poverty on different life domains of subjective well-being, stressing the role of regional characteristics in individual perceptions.

Our analysis contributes to the growing literature in several ways. First, we investigate the impact of poverty adaptation for different levels of income variations in poor individuals. Second, it extends earlier empirical studies, by providing evidence of poverty adaptation as a regional phenomenon and not solely at the country level. Third, in addition to considering the impact of being poor on individual life satisfaction, various aspects of poverty are considered, such as the intensity and poverty adaptation. Moreover, an overall measure of life satisfaction is accompanied by some domains of economic and social satisfaction, creating a complete picture of the role poverty plays in the lives of individuals. Finally, we propose a statistical matching approach to overcome the lack of a unique survey containing information on individual SWB and MWB at the country level.

2. Statistical Matching

For the purpose of this study, there is no unique survey collecting all the information needed. Information about Italian economic conditions and the life domain satisfaction of households are collected yearly by the Italian Office of Statistics (ISTAT) through two different Italian surveys: Aspect of Daily Life (ADL) and Household Budget Survey (HBS). In the first questionnaire, people are asked to provide information about a wide set of habits and aspects of life, including a specific focus on the satisfaction level about different life domains, such as economic conditions or social aspects. The second survey, ISTAT quantifies monthly expenditure habits of Italian households, including on all possible expenditure aggregates of families (e.g. foods, dwelling expenditures, transportation). Since the surveys refer to two different samples of individuals, changing every year, a unique dataset has been built referring to statistical matching techniques (D'Orazio *et al.*, 2006). Both the surveys provide information on the urbanization level of place where people live even if there are some differences.

The idea behind statistical matching techniques (also known as data fusion), is to merge the two independent samples, based on two main facts: the datasets of interest contain information on both common variables and variables that are not jointly observed; the datasets are disjointed sets of units. In this way, the procedure aims to combine the information collected by two different sources, using communalities in the two sets of data. There are two distinct ways to pursue this integration. The first one is known as a Micro approach. Here the objective is to build up a unique file where all the variables of interest are recorded. The second set is given by the so-called Macro approaches. In this case the separate datasets are used to obtain a direct estimation of the unknown joint distribution function of the variables under analysis. The choice between the two classes of approaches is representative of different aims and assumptions described by D'Orazio, Di Zio and Scanu (2006). Mainly motivated by the idea of controlling several critical aspects in the poverty-wellbeing nexus representative of the level of complexity of the phenomenon, this study refers to the class of micro approaches. Specifically, the matched dataset of wellbeing, poverty and adaptation is obtained using micro non-parametric statistical matching techniques.

In general, let (X, Y, Z) be a random variable with associated unobservable joint density f(x,y,z). Then consider the idea of observing X, Y and Z, as generated from the density f(x,y,z) in two separate datasets. The first sample, i.e. A, consists of n_A iid observations for which we observe the realizations of X and Y; whilethe second sample, called B, collects exclusively X and Z for n_B units. The objective is then to use common information in the two samples (i.e. information about X) to obtain a final comprehensive collection of data.

Without making assumptions on the joint unobservable distribution of the matched variables, in this study we consider the set of non-parametric methodologies, and in particular the distance hot deck procedure (one of the most commonly used micro approaches in empirical applications, see Ridder and Moffit (2007) for a review), as a natural solution. Moreover, Marella, Scanu and Conti (2008) found that when distance hot deck procedures are used the matching noise due to imputation, decreases as the sample size of the donor sample increases, therefore, making this technique attractive.

Operatively, the satisfaction scores of ADL (the donor – largest survey) are imputed to the HBS records in accordance with the similarities calculated on the so-called matching variables, i.e. a subset of common variables chosen in the two surveys. In particular, as matching variables we considered the age of individuals collected as a 13-level variable, the number of household members, a categorical variable measuring the level of education, marital status (5 levels) and Italian regions. The procedure employed is then refined considering (i) imputation without replacement, and (ii) referring to several donor classes, i.e. restricting the imputation from a specific donor record to a recipient one with the same gender and living in the same macro areas (North, Centre and South of Italy). The resulting matched dataset reports information about 23,002 Italian individuals for 2016.

To evaluate the final results obtained via statistical matching, we use a set of statistical measures to investigate the coherence of the imputation (see D'Orazio *et al.*, 2006 for a review). Specifically, for all the satisfaction scores considered in this study, the values obtained for the total variation distances and Hellinger distances are closed to 0, and Bhattacharyya indexes closed to 1, suggesting the distribution of the target variables (i.e. the life satisfaction scores and life domains satisfaction with economic condition, health condition and leisure) in the final matched dataset has a good level of preservation (results available on request).

3. Modelling Adaptation in the Poverty – SWB Nexus

In line with literature, we estimate micro-econometric satisfaction models in which the subjective well-being of individual i, SWB_i,i=1,…,N, depends on different individual poverty measures, a set of variables proxying adaptation to poverty, a set of individual-level controls and territorial variables. The model is given by:

$$SWB_i = \beta_0 + \sum_{j=1}^{J}\sum_{(k=1)}^{K} \rho_{jk} Poverty_{j,i} * VarEconCond_{(k,i)} + \quad [1]$$

$$+\gamma' \boldsymbol{Ind}_i + \psi' \boldsymbol{Terr}_i + \varepsilon_i, \quad \varepsilon_i \sim iid(0,\sigma^2)$$

where $Poverty_{j,i}$, j=1,...,j, represents the jth variable measuring relative individual poverty, while adaptation is investigated by the interaction of poverty variables with a set of K measures detecting variation in people's economic conditions (i.e. $VarEconCond_{(k,i)}$,k=1,…,K).

To capture different dimensions of poverty we consider the individual counterpart of the Foster-Greer-Thorbecke (FGT) class of decomposable poverty measures (Foster *et al*, 1984, 2010), given by

$$P_{\alpha,i} = \left(\frac{z - x_i}{z}\right)^{\alpha} 1_{x_i \le z} \qquad i = 1,\ldots,N,\ \alpha = 0,1 \quad [2]$$

Where x_i is the equivalent expenditure of the i-th individual, z is the poverty line, and $1_{x_i \le z}$ is an indicator function that assumes a value equal to one is the equivalent expenditure for the i-th individual, x_i, is lower than the poverty line (poor individual), zero otherwise. The parameter α, with α ≥ 0, is a "poverty aversion" parameter. In particular, the higher the value of the aversion parameter, the higher the relevance accounted for in the lower tail of the consumption distribution. Then we consider the $P_{\alpha,i}$ variables as poverty measures by naming them, for sake of simplicity, as the correspondent poverty indexes, that is *incidence* P_0 (i.e.,known as headcount ratio), and *intensity* P_1 (i.e., the poverty gap measure) respectively for α =0,1.

We suggest estimating the role of poverty adaptation by using the question about the variation in economic condition that asks a person to compare his/her economic situation with that of a year ago. The variable, that is measured on a 5-points scale (i.e., Much worse, A little worse, Remained more or less the same, A little improved, Much improved), is then appropriately transformed into dummy variables and combined with the poverty measures P_0 and P_1.

We define two main measures for detecting adaptation. First, we dichotomize the information by creating two dummies: *OldPoor* and *NewPoor*. Specifically, we identify *OldPoor* as poor people entering poverty the year before, those who were poor at time t and described their economic conditions as improved or at least remained more or less the same with respect to the previous year (i.e., *OldPoor* = $P_0 * 1_{\text{VarEconCond>= Remained more or less the same}}$). In this case, we are able to evaluate the overall adaptation effect of being poor for at least one year on own life satisfaction, as done in previous studies (Luo, 2022; Clark *et al.*, 2016). People who are poor at time t and declare an overall worsening in their economic condition are used as a proxy of the new poor in time t (i.e., *NewPoor* = $P_0 * 1_{\text{VarEconCond< Remained more or less the same}}$)[1]. Similarly, we define the poverty intensity of those are identified as new poor (i.e., $P_1 * 1_{\text{VarEconCond<Remained more or less the same}}$) and of people already poor the previous year (i.e., $P_1 * 1_{\text{VarEconCond>= Remained more or less the same}}$). The second set of variables used to investigate adaptation is obtained by exploiting the overall information captured by the original variable. This approach allows us to evaluate the impact of the different levels of adaptation on the individual well-being of being poor and intensity of poverty at time t. Specifically, we create four dummy variables: *Improved* (grouping the first two levels of the variable "Much improved" and "A little improved"), *Unvaried* (corresponding to the answer "Remained more or less the same"), *Worsening* and *Sworsening* (respectively representing the remaining two levels "A little worse" and "Much worse"); each dummy is then multiplied by the poverty measures considered in this analysis.

Following the literature (Clark, 2017) $\boldsymbol{Ind_i}$ is the vector of individual socio-demographic characteristics: *Gender*, a dummy variable equal to one for female;

1. This procedure has a limit however: we are not able to verify whether poor at time t declaring a worsening condition in the last year, were also poor at time t-1, and whether or not poor at time t declaring a better condition in the last year, were poor at time t-1. However, a check on their total spending at time t suggests that these cases are quite negligible.

Age for the age of respondent; *HighEducation*, a dummy variable assuming the value of one for people with the highest levels of education; *Unemployed*, *Retired*, representing two labour-force statuses of being unemployed or being retired; *Married, Divorced, Widower*, to account for the three marital statuses; *nComp*, the number of components in the household.

Finally, in line with Giarda and Moroni (2018) and Lenzi and Perucca (2018, 2021), the specification is further enriched by a set of dummy variables ($\boldsymbol{Terr}_i$) related to geographical and regional aspects, including the North and Center-South divide and the degree[2] of urbanization of people' living environment.

With the aim of measuring regional disparities in the SWB-poverty relationship, the models in Equation 1 are estimated for the whole Italian territory and compared to results obtained from the two macro areas, North vs Centre-South.

4. The Data

Following the ISTAT approach, in our analysis, household expenditures has been transformed into individual spending by applying the Carbonaro equivalence scale (1985; 1990). Then, the definition of relative individual poverty is based on a poverty line equal to the mean per-capita consumption expenditure at the national level (i.e., in 2016 the monthly expenditure equals 636.81). By moving from the household to an individual level, we aim to preserve the individuality and reliability of the SWB scores. Table 1 and Figure 1 present some descriptive statistics on the main variables used in the analysis at the country and macro-areas levels.

The average overall level of life satisfaction in Italian residents is equal to 7.03 and it decreases when we move from North to South (Figure 1). A similar pattern is detected for the economic domain, which has an average of 2.45 (on a 4 point scale), while the mean satisfaction for the health and leisure domains is quite a lot higher; all satisfaction scores reduce in the South of Italy.

Poor people represent 10% of the Italian population, of which, 20% reside in the North, 14% in the Centre and 66% in the South. Intensity of poverty shows similar results, with the highest poverty gaps observed in the South.

As for the variation in economic condition, 62% of individuals declare that their status is stable with respect to the previous year, while 33% reported an overall worsening condition.

2. Following the ISTAT classification of territories, we identify municipalities with less than 50 thousand residents as rural areas, and those with more than 50 thousand inhabitants as urbanized territories. The 12 Metropolitan area are Bari, Bologna, Cagliari, Catania, Firenze, Genova, Milano, Napoli, Palermo, Roma, Torino, Venezia.

Table 1 – Descriptive Statistics

Satisfaction scores			*Individual characteristics*		
	Mean	*sd*		*Mean*	*sd*
Life Satisfaction	7.03	1.58	Gender (Female=1)	0.64	0.48
LDeco	2.43	0.75	Ncomp	2.44	1.13
LDhea	2.92	0.69	Age	49.41	22.18
LDlei	2.77	0.78	HighEducation	0.16	0.37
			Unemployed	0.13	0.34
Poverty measures			Retired	0.23	0.42
P_0 (Incidence)	0.10	0.30	Married	0.32	0.47
P_1 (Intensity)	0.02	0.09	Divorced	0.07	0.25
			Widowed	0.11	0.32
Variation in economic condition			Teritorial aspects		
SImproved	0.00	0.04	Metropolis	0.12	0.33
Improved	0.04	0.19	Urban	0.27	0.44
Unvaried	0.62	0.48	Semi-Rural	0.37	0.49
Worsening	0.26	0.44	Rural	0.24	0.43
SWorsening	0.07	0.25	North	0.43	0.49
			CentreSouth	0.57	0.49

Notes: LS: Life Satisfaction, 1-10, from "Very Dissatisfied" to "Very Satisfied"; LDeco: life domain economic condition; LDlei: free time; LDhea: health condition: 1-4, from "Very Dissatisfied" to "Very Satisfied".

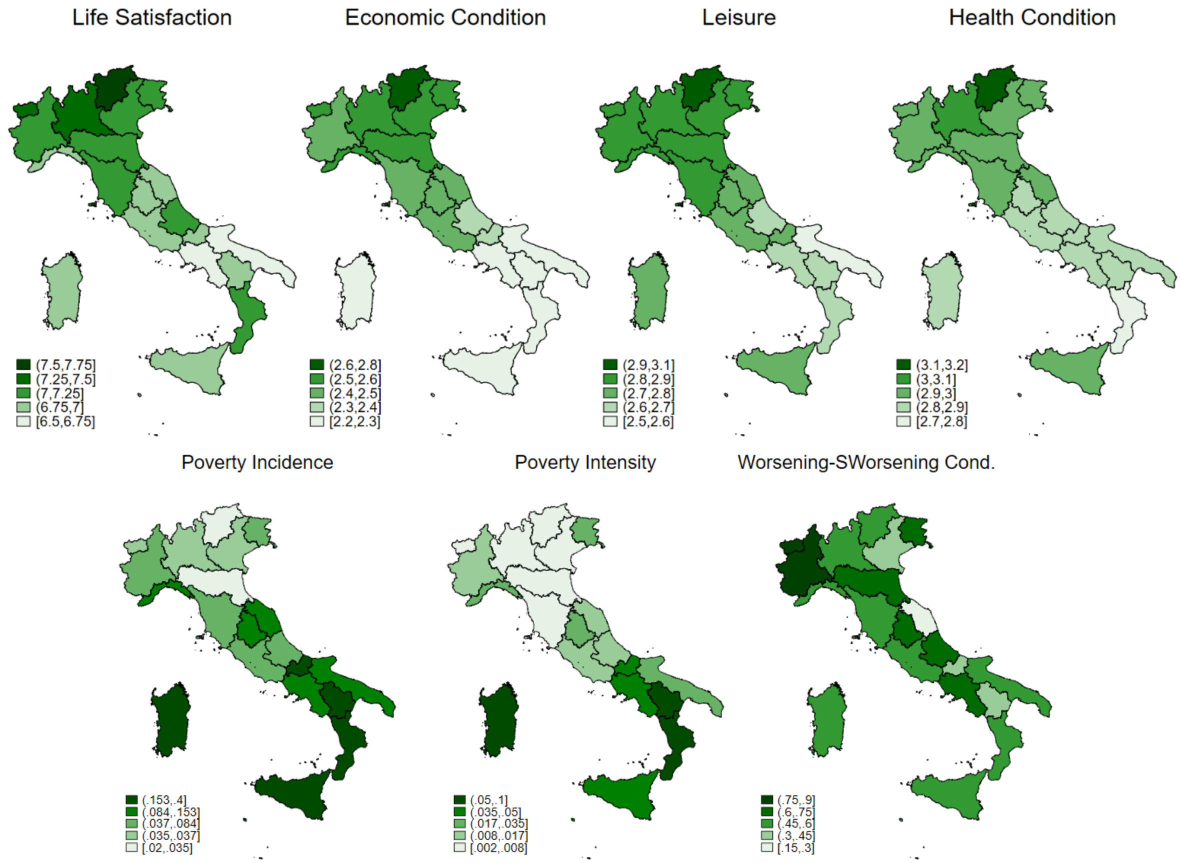
Source: Authors' elaboration

5. Results

5.1. SWB, Poverty Adaptation and Regional Disparities

First, to compare our results with previous findings in the literature and to evaluate the role of regional disparities, we estimate the model in Equation (1) distinguishing between new and old poor people, differentiating in respect to poverty incidence and intensity, and territorial macro-areas (Table 2). In Italy, people who entered poverty at time t (NewPoor) exhibit a large reduction of their SWB, while adaptation is found for people who were poor since at least one year ago (i.e., the coefficients associated to the variable OldPoor are all not significant, meaning that there is not a significant difference between the satisfaction level of people entering poverty the year before and those who are not poor). The negative effect of being a new poor on life satisfaction dramatically

Figure 1 – The Italian Map of Life Satisfaction, Poverty Measures and Economic Condition Variations



Source: Authors' elaboration

Table 2 – Model Estimates for SWB and Poverty Adaptation Across Territorial Areas

	By Incidence			*By Intensity*		
	Italy	*North*	*Centre-South*	*Italy*	*North*	*Centre-South*
OldPoor	0.062	-0.051	0.091	0.197	-0.307	0.297
NewPoor	-0.556***	-0.677***	-0.517***	-1.513***	-2.191***	-1.311***
Gender	0.028	0.008	0.042*	0.026	0.006	0.041*
Ncomp	0.010	-0.005	0.017	0.010	-0.003	0.016
Ln(Age)	-0.294***	-0.150*	-0.401***	-0.296***	-0.151*	-0.402***
HighEducation	0.261***	0.181**	0.327***	0.267***	0.182**	0.336***
Married	0.224***	0.223***	0.230***	0.223***	0.223***	0.228***
Divorced	-0.058	-0.171**	0.041	-0.058	-0.166*	0.039
Widower	-0.232***	-0.170**	-0.246**	-0.227***	-0.167**	-0.239**
Unemployed	-0.168***	-0.136*	-0.210***	-0.175***	-0.133*	-0.221***
Retired	0.060	0.014	0.070	0.060	0.012	0.072
Semi-Rural	-0.230***	-0.189***	-0.272***	-0.232***	-0.185***	-0.277***
Urban	-0.184***	-0.065	-0.281***	-0.182***	-0.061	-0.281***
Metropolis	-0.210***	-0.197**	-0.237***	-0.208***	-0.193**	-0.236***
North	0.271***			0.276***		
Const	8.105***	7.862***	8.517***	8.103***	7.856***	8.513***
Cluster s.e. by regions	YES	YES	YES	YES	YES	YES
Observations	23,002	9,834	13,168	23,002	9,834	13,168
Loglik	-42717	-18158	-24524	-42734	-18157	-24540
AIC	85466	36329	49071	85499	36329	49102
BIC	85595	36380	49154	85628	36379	49185

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10.

Source: Authors' elaboration

increases in intensity (if the relative poverty line gap grows one unit, the overall life satisfaction reduces significantly by 1.513 points); while adaptation is found for people only poor at time t-1. This result in part diverges from previous literature, where adaptation has not been detected (Clark *et al*, 2016), or at least since 2 years (Luo, 2022); this difference may be due to the nature of our data, which is a cross- section survey providing information on the poverty condition at the time t and only one year prior, while the majority of studies on adaptation consider poverty from 0-1 years, 2-3 years and so on.

Regarding macro-areas, similar to the whole territory, estimates confirm poverty adaptation for people who were poor, since at least one year prior. Conversely, the new poor living in the Northern regions are the most sensitive to poverty, reporting a greater aversion to this condition with respect to citizens in the Centre-South of the country (-0.677 vs -0.517); moreover, new poor in the North show a very high sensitivity to the intensity of poverty, with respect to the magnitude observed in the South. Findings confirm a different response of SWB for new entries into poverty across the Italian regions, which is higher in richer regions, underscored by a greater sensitivity to poverty and an increasing aversion to inequality of the new poor living in the North. Therefore, the reference to peers in wealthy regions seems to lead new poor individuals to suffer more from their condition, and especially if the intensity of the new condition is high and far from the poverty line.

As for demographic variables, estimates show positive effects on well-being for both high education levels and living with a family (Felton, Graham, 2006). Being out of the labour-market has a negative effect on individual well-being, and life satisfaction decreases with age (Pinquart, Sörensen, 2000). Macro area dummies confirm the expected divergence between North and Central-Southern territories (with a significant positive coefficient estimated for the richest Italian regions, i.e. Northern areas); living in metropolitan areas reduces well-being (all these results are confirmed by the following model estimates, and are available on request from the Authors).

Secondly, we estimate models in Equation (1) by considering the different levels of variation in economic conditions over the whole sample of poor individuals (Table 3), identified by the dummies *Improved, Unvaried*, *Worsening* and *Sworsening,* multiplied by poverty incidence and intensity. In Italy, we find that the condition of being poor has a different impact on SWB with respect to the economic condition in the previous period. Subjective well-being turns out to be significantly sensitive to the poor condition, if this condition is worsening with respect to the past (SWB significantly reduces by 0.360) and more intense if the variation is much worse (the decrease equals -0.857). The impact on SWB of worsening poverty intensity is much more relevant: life satisfaction reduces by 1.027 if the condition is worsening and the decrease is double (-2.041) if the reduction in economic conditions is much worse. Overall, if the economic condition improves or remains stable with respect to the past, the impact on life satisfaction is negligible. These findings provide new insights on adaptation to poverty: if there are no changes or one's own economic conditions are improving, the effects on SWB is null (not statistically significant), confirming adaptation; if one's own condition gets worse, this has a negative and significative impact on SWB.

When the analysis moves to the two macro-areas, regional disparities in the response of SWB to variations in poverty become more evident. Poor people

Table 3 – Model Estimates for SWB and Level of Poverty Adaptation Across the Territory

	By Incidence			*By Intensity*		
	Italy	*North*	*Centre-South*	*Italy*	*North*	*Centre-South*
Improved	0.280	-0.184	0.523	0.607	-2.440	2.364*
Unvaried	0.054	-0.041	0.077	0.186	-0.109	0.245
Worsening	-0.360***	-0.351*	-0.368**	-1.027**	-1.532*	-0.889
Sworsening	-0.857***	-1.096***	-0.759***	-2.041***	-2.872***	-1.772***
Socio-demographic	YES	YES	YES	YES	YES	YES
Cluster s.e. by regions	YES	YES	YES	YES	YES	YES
Observation	23002	9834	13168	23002	9834	13168
Loglik	-42702	-18150	-24517	-42727	-18154	-24535
AIC	85439	36314	49055	85490	36322	49091
BIC	85584	36364	49138	85635	36372	49174

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10.

Source: Authors' elaboration

living in the North express the highest negative response of SWB to a significant deterioration of their economic condition (-1.096 vs -0.759 of poor in the Center-South of Italy). However, these regional differentials become more relevant when the intensity of being poor is considered: as the economic condition exacerbates, there is a large reduction in SWB in the North, with a magnitude almost double that observed for poor people living in the Centre – South. For poor people in the Centre-South, an improvement in their economic condition leads to a positive effect on their life satisfaction, signalling that these people are sensitive to a bettering of their poverty intensity. Again, the comparison with peers in the richest regions of the North negatively affects the perceived wellbeing of the poor individuals. Further, poor people tend to compare their own conditions to others living in the neighbourhood: where poverty is a limited phenomenon, as in the North, poverty adaptation is much harder and the magnitude of this effect increases as the intensity of poverty increases.

5.2. Life Domains, Poverty Adaptation and Regional Disparities

Even if the relationship between poverty adaptation and economic conditions is known in the literature (Lou, 2022), its role in other aspects of an individual's life, to our knowledge, has not yet been investigated. To fill this gap, we estimate

Table 4 – Model Estimates for Life Domains and Poverty Adaptation Across Territory

		By Incidence			By Intensity		
		Italy	*North*	*Centre-South*	*Italy*	*North*	*Centre-South*
LDeco	OldPoor	-0.033	-0.280	0.038	-0.314	-1.784***	0.002
	NewPoor	-1.189***	-1.612***	-1.069***	-3.160***	-4.369***	-2.848***
Ldlei	OldPoor	-0.022	-0.182**	0.016	-0.119	-0.587	-0.030
	NewPoor	-0.285***	-0.428***	-0.254***	-0.605***	-0.899***	-0.548***
Ldhea	OldPoor	-0.197***	-0.266	-0.176**	-0.679***	-1.321	-0.536***
	NewPoor	-0.589***	-0.815***	-0.557***	-1.472***	-2.321***	-1.319***
Socio-demographic		YES	YES	YES	YES	YES	YES
Cluster s.e. by regions		YES	YES	YES	YES	YES	YES

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10.

Source: Authors' elaboration

models in Equation (1) to capture three different aspects of life: the economic, leisure and health domains.

Regarding the whole country, satisfaction in the economic domain is impacted the most by poverty: new people entering poverty signal a reduction in economic satisfaction of 1.189, which grows to -3.160 if the intensity of poverty is considered; moreover, adaptation to poverty is detected for people who were poor at time t-1 (Table 4). Looking into the territorial analysis, the divided response, previously detected for SWB, is confirmed: new poor people in the North of Italy are more sensitive to both the condition and the intensity of poverty. However, a novel and interesting result emerges: adaptation to poverty is rejected for people living in poverty since at least one year ago and living in the North; this finding confirms the high sensitivity to poverty of people living in richer areas.

The impact of being a new poor and the related intensity on satisfaction for leisure activities register the lowest value (-0.285 and -0.605, respectively, for Italy), even if statistically significant; again, for this domain, we find a territorial divide in the magnitude of the response. Once again, we note a higher sensitivity of satisfaction with leisure activities to poverty in the North, where being poor at least for one year has a negative impact on this domain.

Satisfaction with health is the only domain negatively affected both by NewPoor and OldPoor; thus, the hypothesis of poverty adaptation is strongly rejected. People entering into poverty show the highest reduction in their satisfaction for health, which is on average three times that observed for old poor (-0.589

Table 5 – Model Estimates for Life Domains and Level of Poverty Adaptation Across the Territory

	By Incidence			By Intensity		
	Italy	*North*	*Centre-South*	*Italy*	*North*	*Centre-South*
			Economic condition			
Improved	0.155	-0.729	0.547	0.171	-5.516**	3.229
Unvaried	-0.039	-0.247	0.024	-0.323	-1.466***	-0.070
Worsening	-0.849***	-1.146***	-0.776***	-2.418***	-3.517***	-2.139***
Sworsening	-1.750***	-2.211***	-1.586***	-4.032***	-5.385***	-3.681***
			Leisure			
Improved	-0.057	-0.610	0.275	-0.707	-2.697	0.588
Unvaried	-0.020	-0.149	0.008	-0.099	-0.397	-0.044
Worsening	-0.216***	-0.359**	-0.195**	-0.513	-0.941***	-0.430
Sworsening	-0.392***	-0.518***	-0.352*	-0.706***	-0.857*	-0.676*
			Health condition			
Improved	-0.529	-1.372	-0.128	-1.230	-5.493**	1.048
Unvaried	-0.183***	-0.184	-0.177**	-0.659***	-0.990	-0.577***
Worsening	-0.430***	-0.569**	-0.428***	-1.108***	-1.852**	-1.000**
Sworsening	-0.842***	-1.127***	-0.775***	-1.862***	-2.780***	-1.667***
Socio-demographic	YES	YES	YES	YES	YES	YES
Cluster s.e. by regions	YES	YES	YES	YES	YES	YES

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10.
Source: Authors' elaboration

and – 0.197 for the whole country, respectively). As before, the North shows a higher sensitivity to poverty incidence and intensity, but it is limited to the new poor. Conversely, estimates reveal that poverty adaptation to the health domain is strongly rejected in the Centre -South of Italy, where the health care system is dramatically inefficient (Barra *et al.* 2022).

Considering the different levels of variation in the perception of current economic condition compared to the past (Table 5), estimates for the economic domain confirm an increase in the negative response as poverty worsens along with the intensity of the poverty condition aggravated. As before, this negative response is more relevant for the poor living in the North.

The impact that the worsening of poverty incidence and intensity has on satisfaction with leisure activities is less relevant. When we move to two macro-areas, regional differences in the response of leisure satisfaction are confirmed, even if these differences are lower in general.

The health domain appears to be the most sensitive to variation in the poor's economic condition: a negative effect is detected on health satisfaction also for poor people reporting a stable economic condition with respect to the past. In particular, this aspect is significant in the Centre-South of the country, confirming the clear regional divide in the health care system across Italy.

6. Conclusions and Further Developments

This study investigated the regional diversity of the SWB-poverty adaptation nexus, by considering different life domains.

In general, adaptation is rejected for people already in poverty during the previous year or when poor people find themselves in a worse condition over the last year; these effects are stronger when economic and health life domains are considered.

Our results confirm that people's response to poverty adaptation varies across territories due to economic and social diversities, confirming the divide between the North and Centre -South of Italy (Giarda, Moroni, 2018). We detected a strong impact of poverty measure on the SWB of people living in the North, with a higher level of intensity than observed in the South. Findings suggest that people tend to compare their own conditions to others living in the neighbourhood: where poverty is a limited phenomenon, the impact on the poor is much higher and the magnitude of this effect increases as the intensity of poverty increases.

As for life domains, the highest level of sensitivity is detected for economic conditions, and this effect is particularly evident in the Northern regions. The leisure domain is in generally less affected by poverty conditions, and the differences in the magnitude of the nexus between Northern and Central-Southern areas are low. Health is the only domain negatively affected by being poor at time t and in the previous year, strongly rejecting the hypothesis of poverty adaptation. In particular, this aspect is relevant in the Centre-South of the country, confirming the high disparity in the health care system across Italy.

Findings suggest some policy recommendations. First, place-based policies aiming at contrasting poverty and poverty adaptation should be considered. Second, the incidence and intensity of poverty are more related to the economic and heath spheres of the people, which is where policies should aim, especially to reduce regional disparities.

An interesting suggestion araising from this research is the creation of panel data to investigate poverty adaptation in the long-run. This requires a novel database obtained by a dynamic statistical matching approach. However, as pointed out by D'Orazio *et al.* (2006), almost all of the existing matching methods assume a cross-sectional dataset. Despite the few attempts at cross-section time series matching (Imai *et al.*, 2021; Simonson *et al.* 2012) all the proposed procedures involved at least one of the matching datasets with a longitudinal structure. We are actually studying a new procedure for the fusion of data of a (pure) cross-sectional nature, involving additional information coming from secondary sources. This approach will allow the current study to be extended, from considering poverty adaptation, multidimensionality in SWB and regional disparities, to a dynamic setting.

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Adattamento alla povertà, multidimensionalità del benessere e disparità regionali in Italia: un approccio di matching statistico

Sommario

Le profonde trasformazioni che interessano oggi le economie si ripercuotono sul benessere degli individui, che rappresenta la base per lo sviluppo sostenibile e la riduzione della povertà. Il benessere è un concetto multidimensionale e la capacità di misurarne i diversi aspetti è di cruciale importanza per definire politiche adeguate. Questo capitolo si focalizza sull'analisi di come il benessere soggettivo delle persone si adatta alla povertà, approfondendo l'impatto che una variazione della condizione economica, rispetto all'anno precedente, ha sia sulla soddisfazione complessiva sia su quella di diversi ambiti della vita. Per indagare se esistano disparità regionali in queste relazioni, l'analisi viene sviluppata per l'intero Paese e per le principali macroaree (Nord vs Centro-Sud). Per superare il problema di ottenere informazioni sulla povertà e sul benessere soggettivo, proponiamo un approccio di matching statistico. I risultati mostrano che l'ipotesi di adattamento alla povertà è rifiutata per gli individui appena entrati in povertà o quando le condizioni di una persona povera peggiorano nell'ultimo anno. Le stime evidenziano l'esistenza di differenze regionali significative nella relazione tra SWB e

adattamento alla povertà, in particolare per i domini legati agli aspetti economici e alla salute. I risultati possono essere utilizzati per la definizione di politiche territoriali volte a ridurre le disparità nelle condizioni di vita dei residenti.

Spillover Effects in the Innovative Activity of Italian Start-ups: a Spatial Stochastic Frontier Approach

*Federica Galli**

Abstract

Start-ups play a fundamental role in countries' economic growth since they stimulate inventiveness and market dynamics and in periods of deep transformations, it becomes even more important to understand what contributes to determining their survival in the market. In this framework, innovation is a key factor for favouring incumbent firms' positive performance, survival and competitiveness. Besides internal investments in R&D activity and the presence of skilled and qualified personnel, also the external environment in which incumbent firms are located can represent a key source of new knowledge thanks to knowledge and learning spillovers occurring in innovative clusters. Therefore, in this paper, we evaluate the role of knowledge spillovers in affecting Italian start-ups efficiency level differentiating between spatial effects arising from intangible investments and firms' patenting activity. Moreover, we also consider whether productivity and input spillovers occur across neighbouring start-ups. To achieve these goals, we use georeferenced firm-level data on Italian innovative start-ups in the period 2018-2020 and we estimate a spatial stochastic frontier model that allows considering different sources of spatial dependence. The results of the analysis can help policymakers design plans and policies aimed at favouring start-ups' competitiveness by exploiting firms' interaction and cooperation.

1. Introduction

Start-ups are fundamental for countries' economic growth since they stimulate inventiveness and market dynamics, increase productivity and satisfy new consumers' needs by producing highly technological and up-to-date products (Antonietti, Gambarotto, 2020). In periods of crises and profound transformations, the identification of the sources of start-up's survival in the market is crucial. In Italy, policymakers are paying particular attention to innovative start-ups due to their key role in (re)launching and promoting the national economy. In

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particular, the 'Italian Start-up Act' issued by the Italian government by Decree Law 221/2012 in 2012 recognizes the key role of entrepreneurship and innovation as drivers of sustainable economic growth. Between the different factors affecting entrepreneurs' propensity to start a new business, empirical studies have identified the key role of the context in which new firms originate such as the personality traits of the population, the social acceptance of the entrepreneur status and the regional entrepreneurship culture (Stuetzer *et al.* 2017; Kibler *et al.* 2014; Fritsch, Wyrwich, 2014, 2017; Capello, Lenzi, 2016). However, a large number of start-ups fail within the first three years of activity due to inappropriate technological, market and institutional conditions (Acs *et al.*, 2016).

One of the main engines for start-ups' survival and competitiveness can be identified by firms' innovative activity. Indeed, despite the difficulty of new firms to survive the first years of activity, innovation can play a fundamental role in determining incumbent firms' positive performance. Between internal innovative factors, R&D investments, patents and qualified personnel play a crucial role in shaping start-ups' innovation process. First, R&D activities are characterized by high uncertainty because firms do not know in advance if R&D investments will achieve some positive and exploitable results. Moreover, research activity performed by start-ups is even more risky because incumbent firms often make R&D investments in an informal, non-systematic and non-organic way (Matricano, 2020a, 2020b). However, research activity is a fundamental first step to achieving higher performances (Galizzi, Venturini, 1996; Leiponen, 2000; Avermaete *et al.*, 2004; Frick *et al.*, 2019). A second factor that can allow start-ups to reach superior returns is the presence of qualified personnel such as scientists and engineers (Huiban, Bouhsina, 1998; Leiponen, 2000). Indeed, adequately trained and skilled people can contribute better to R&D activities compared to general technicians and employees thanks to their distinctive competencies (Selznick, 1957). Finally, holding a patent is usually a positive signal of start-ups quality and strength because it allows new ventures to achieve higher returns protecting their innovative efforts thanks to property rights for the newly developed products (Mason, Stark, 2004; Hottenrott *et al.*, 2016; De Rassenfosse, 2012). However, patenting is usually too expensive for incumbent entrepreneurs and bigger companies are more willing to hold patents with respect to small start-ups (Andries, Faems, 2013; Frietsch *et al.*, 2013; Greenberg, 2013).

Besides the importance of internal innovative activity, also the external environment in which firms are embedded plays a crucial role in determining new ventures' performance due to the relevance of learning and knowledge spillovers in stimulating incumbent firms' innovative activity (Acs *et al.* 2009; Jacobs, 1969). Knowledge spillovers have been defined by Griliches (1992, p. 29) as "*working on similar things and hence benefiting much from each other's research*". Geographic proximity is fundamental for the transmission of new knowledge because ideas and innovations are best transmitted via face-to-face interactions and individuals contact (von Hipple, 1994). Indeed, it is easy to share information in an era where the world is continuously in touch thanks to a highly developed telecommunication network but flows of knowledge work in a different way. Indeed, knowledge is difficult to explain and codify through digital channels and, as Glaeser *et al.* (1992, p.1126) stated: "*intellectual breakthroughs must cross hallways and streets more easily than oceans and continents*". Thus, knowledge spreads better within geographical boundaries because of its tacit and uncodified nature (Baptista, 2000). Therefore, also investments in innovative activities performed by other firms and public organizations in the neighbourhood contribute to positively influencing peers (Link, Rees, 1990; Audretsch, Belitski, 2020) and this is particularly true for start-ups due to the importance of external knowledge inputs in the first business stages (Audretsch *et al.*, 2021). In particular, being located in highly innovative areas encourages both start-up formation and subsequent performance because growing and promising clusters attract new businesses, talented entrepreneurs and individuals with relevant skills and new ideas and knowledge tend to spill over stimulating new ventures' innovative activity (Porter, 2000).

Spatial spillovers across nearby firms can first of all depend on emulation processes. Indeed, less efficient producers can attempt to emulate the best procedures and practices of the productivity leader in closely related industries gaining a productive advantage (Syverson, 2011). Crespi *et al.* (2007) and Keller and Yeaple (2009), showed that locating a firm nearby to a multinational company helps in intercepting more easily free information flows while Leary and Roberts (2014) demonstrated that peer effects are more evident between small and medium enterprises (SME) because for SMEs it is easier to obtain information from closest firms. Therefore, small firms located in highly innovative clusters are often able to easily start a new competitive business in highly technological markets such as biotechnology and computer software, undertaking a negligible amount of R&D investments thanks to knowledge spillovers originating from bigger companies belonging to the cluster (Audretsch, 1995). The intensity at which new knowledge is assimilated depends on the absorptive capacity of firms. According to Yang (2010), absorptive capacity is the most important prerequisite for success because identifying new sources of knowledge, assimilating, and applying them to commercial ends guarantees a successful knowledge transfer.

Despite many studies recognized the importance of spillover effects in shaping start-ups' productive performance, to our knowledge, there are still no studies investigating the role of both internal and external sources of innovation in determining the level of efficiency of incumbent firms. However, both for entrepreneurs and local governments, it would be fundamental to be aware of the role of knowledge spillovers originating from different sources of firms' innovative activity in shaping neighbouring start-ups' performance in order to design plans and programs aimed at supporting start-ups' formation and survival. Therefore, in this paper, we aim at measuring the impact of both internal innovation and spatial effects arising from neighbouring start-ups' innovative activity on incumbent firms' efficiency levels. Specifically, we concentrate on Italian innovative start-ups in the time period 2018-2020 and we estimate the spatial Durbin stochastic frontier model introducing spillover effects in the determinants of firms' efficiency introduced by Galli (2023). Indeed, this novel spatial stochastic frontier model allows evaluating the specific spatial effects arising from each inefficiency determinant introducing the spatial lag of the inefficiency variables. Moreover, besides capturing spillover effects related to firms' efficiency, it also allows to identify productivity and input spillovers affecting neighbouring firms' performance. As a result, clear and distinct insights on the different spatial effects can be obtained distinguishing between spillover effects affecting the level of productivity of firms and spatial effects related to firms' efficiency level.

To sum up, this study extends the current literature on start-ups' performance in different ways. First, to our knowledge, this is the first paper investigating the impact of external sources of innovation on start-ups' efficiency levels. Second, besides considering spillover effects related to firms' innovative activity, we also evaluate spatial effects affecting firms' productivity level, i.e. productivity and input spillovers. Indeed, greater availability of specific products, input suppliers, assets and workers with industry-specific skills in a certain territory may favour input spillovers (Marshall, 1890) while start-ups' productive performance may be influenced by the one of neighbours due to the transmission of best practices between peers, collective behaviours resulting from face-to-face relationships, learning from others, and firms' adoption of new similar technologies (Skevas, Lansink, 2020). The results of our analysis indicate that while positive and significant knowledge spillover generate from neighbouring start-ups' intangible investments, spillover effects related to patents are negative but non-statistically significant. Policymakers can therefore rely on these insights to design proper policies and plan to favour start-ups' innovative activity promoting interaction, cooperation and exchange of ideas between neighbours.

2. Econometric Approach

In order to obtain detailed insights on the different kinds of spatial spillover effects affecting start-ups' productive performance we estimate the spatial stochastic frontier model for panel data introduced by Galli (2023). The first characteristic of this novel spatial specification consists in introducing the spatial lag of each inefficiency determinant, allowing the evaluate the specific spillover effects arising from each variable that contribute to determining the inefficiency level of neighbours. The second characteristic concerns the comprehensiveness of the model specification. Indeed, it introduces three different spatial terms allowing to capture productivity spillovers, input spillovers and spatial effects related to the determinants of firms' inefficiency level. Thus, by estimating this model, it is possible to evaluate whether productivity and input spillovers affect the productive performance of neighbouring start-ups as well as to investigate the role of knowledge spillovers arising from start-ups' innovative activity in shaping peers' inefficiency level. The model specification is defined as in Equations (1-4) with i=1,…,N and t=1,…,T indicating the spatial unit index and the time index.

$$Y_{it} = X_{it}\beta + \rho\sum_{j=1}^{N} w_{ij} Y_{jt} + \sum_{j=1}^{N} w_{ij} X_{jt}\theta + v_{it} - u_{it} \qquad [1]$$

$$v_{it} \sim i.i.d.N\left(0, \sigma_v^2\right) \qquad [2]$$

$$u_{it} \sim i.i.d.N^{+}\left(\mu_{it}, \sigma_u^2\right) \qquad [3]$$

$$\mu_{it} = Z_{it}\phi + \sum_{j=1}^{N} w_{ij} Z_{jt} \qquad [4]$$

Specifically, Y_{it} indicates the productive output of the i-th firm at time t, X_{it} represents a ($1 \times k$) vector including the k production inputs used by firm i at time t with related parameter vector β ($k \times 1$), ρ is the scalar parameter associated with the spatial lag of the dependent variable, allowing to capture global spatial spillovers, w_{ij} refers to the generic element of the block diagonal spatial weight matrix W ($NT \times NT$) containing positive spatial weights to identify neighbouring spatial units (indexed by j=1,…,N) and zero elements on the main diagonal, θ is the parameter vector ($k \times 1$) referring to the spatial lag of the input variables capturing exogenous local input spillovers. Following the classical specification for the error term ε_{it} as being composed by two independent components (Aigner *et al.*, 1977), v_{it} represents the random error and it is assumed to follow a normal distribution with zero mean and variance σ_v^2 as shown in Equation (2) while u_{it} is the inefficiency error term identifying the distance from the productive output of each firm given the level of inputs to the optimal frontier due to technical inefficiency and, in this framework, it is usually assumed to follow a truncated normal distribution with mean u_{it} and variance σ_v^2 as shown in Equation (3). Finally, following the modelling approach introduced by Battese and Coelli (1995) and modified in order to capture spatial effects related to the inefficiency determinants, the mean u_{it} of the inefficiency term u_{it} in Equation (4) is modelled as function of m exogenous variables (Z_{it}) representing the inefficiency determinants with associated parameter vector ϕ ($m\times1$) and of their spatial lag with related parameter vector δ ($m\times1$), allowing to identify spatial dependence arising from the determinants of technical inefficiency of nearby firms.

To estimate the model in Equations (1-4) the two variance parameters should be reparametrized as $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u^2/\sigma^2$ and consistent parameter estimates can be found by implementing a likelihood-based approach. In particular, being the two error terms independent, the joint probability density function of v_{it} and u_{it} can be obtained as the product of the two marginal distributions (i.e. normal and truncated normal, respectively). Subsequently, substituting in the joint probability density function of v_{it} and u_{it} and u_{it} the expression v_{it} and $v_{it}=\varepsilon_{it}-u_{it}$, the joint probability density function of u_{it} and ε_{it} can be obtained. Then, the joint probability density function of ε can be found integrating out u_{it} and multiplying all the marginal distributions of ε_{it} for with i=1,…,N and t=1,…,T. Starting from the joint probability density function of ε, the likelihood function can be obtained as the product of $f_\varepsilon(\varepsilon)$ and the determinant of the Jacobian of the transformation from ε_{it} to Y_{it} in order to take the endogeneity deriving from the inclusion of the spatial lag of the dependent variable into account. The parameter estimates can be found maximising the loglikelihood function using numerical algorithms implemented in standard statistical software. More details on the underlying modelling assumptions and the estimation technique can be found in Galli (2023).

However, in spatial models introducing the spatial lag of the dependent variable, the β estimates cannot be interpreted as marginal effects because changes in the generic regressor X_r of firm i also affect the production output of firm j (Elhorst, 2014). Therefore, also in this case, the marginal effects have to be computed separately, and in particular, they are contained in the matrix on the right-hand side of Equation (5) representing the first partial derivative of Y with respect to the generic regressor X_r (r=1,…,k).

$$\frac{\partial Y}{\partial X_r} = \left(I_{NT} - \rho W\right)^{-1}\left(I_{NT}\beta_r + W\theta_r\right) \qquad [5]$$

In order to summarize the information contained in that matrix, LeSage and Pace (2009) proposed to compute the marginal effects of the independent variable X_r on Y differentiating among direct, indirect and total effects. In particular, they proposed to identify the direct effect of the X_r on Y as the average of the diagonal elements of the matrix on the right-hand side of Equation (5), the indirect effect as the average of the sum of the non-diagonal elements of that matrix, and the total effect as the sum of the direct and the indirect effects.

As for the β estimates, also the ϕ estimates related to the inefficiency determinants cannot be interpreted as marginal effects due to the introduction of the spatial lag of the dependent variable. Thus, the marginal effects can be computed starting from the matrix on the right-hand side of Equation (6) representing the first derivative of the inefficiency level with respect to the generic determinant Z_r with r=1,…,m.

$$\frac{\partial u}{\partial Z_r} = \left(I_{NT} - \rho W\right)^{-1}\left(I_{NT}\,\phi_r + W\delta_r\right) \qquad [6]$$

Starting from that matrix and following LeSage and Pace (2009), the marginal effects of Z_r on u can be computed as before. Thus, the direct effect of Z_r on u can be computed as the average of the diagonal elements of the matrix on the right-hand side of Equation (6), the indirect effect as the average of the sum of the non-diagonal elements of that matrix, and the total effect as the sum of the direct and the indirect effects. Finally, in order to compute the related standard errors or t-values, it is possible to simulate the distribution of the direct, indirect and total effects based on the variance-covariance matrix obtained from the estimation procedure or, alternatively, they can be computed using the delta method.

Starting from the estimated coefficients, the technical efficiency scores can be computed following the method proposed by Battese and Coelli (1998) as $TE = E(exp\left(-u_{it}\right) \mid \varepsilon_{it})$. In particular, technical efficiency scores equal to zero will indicate fully inefficient firms while fully efficient firms will obtain a value of 1.

3. Data and Empirical Model

The data used in this paper are collected from the AIDA Bureau Van Dijk database, being the only one that provides information both on the consolidated accounts of Italian companies and on their geographical location. In particular, we considered all data on Italian innovative start-ups in the time period 2018-2020, where innovative start-ups are defined by Decree Law 221/2012 as those firms operating for at least 48 months, owned directly for at least 51% by physical subjects, with a turnover rate fewer than 5 million euros and with the social aim of developing innovative products and/or services with a high technological content (Colombelli, 2016). Overall, our final sample consists of 1301 firms observed over three years.

The specification of the empirical model is shown in Equations (7-8) for i=1,…N and t=1,…T. The frontier function in Equation (7) is modelled as a Cobb-Douglas function following a production function approach.

$$Y_{it} = \beta_0 + \rho\sum_{j=1}^{N} w_{ij}Y_{jt} + \beta_L L_{it} + \beta_K K_{it} + \beta_t t + \sum_{j=1}^{N} w_{ij}L_{jt}\theta_L + \sum_{j=1}^{N} w_{ij}K_{jt}\theta_K + v_{it} - u_{it} \qquad [7]$$

Specifically, Y_{it} represents the productive output of firm i at time t and it is measured as the logarithm of the value added; the two input variables L_{it} and K_{it} are defined respectively as the logarithm of total salaries paid to the staff and of fixed capital; t represents the time trend and takes value 1 for the year 2018, 2 for 2019 e 3 for 2020. We include in the model specification both the spatial lag of the dependent variable and the spatial lag of the inputs to capture respectively productivity and input spillovers through ρ, θ_L and θ_K. While ρ measures the overall global level of spatial dependence related to firms' productivity level, the θ parameters identify local spatial dependence arising from input variables. To identify neighbouring start-ups we define the spatial weight matrix W as a row-standardized inverse distance matrix truncated at 50 kilometres. Thus, the spatial weights w_{ij}, before row-normalization, take positive values equal to $1/d_{ij}$ where d_{ij} indicates the distance between each pair of spatial units i, j and zero values in the main diagonal and for spatial units that are more than 50km away. Indeed, spillover effects are usually assumed to occur at the local level because firms' interaction and emulation need face-to-face contact, local cooperation and individual contact (Griliches, 1992). Finally, v_{it} is the random error component being distributed as a normal random variable with zero mean and variance σ_v^2 while u_{ij} represents the inefficiency error component and following Battese and Coelli (1995) it is assumed to follow a truncated normal distribution with mean μ_{ij} and variance σ_u^2. The mean of the inefficiency error term is modelled as a function of some exogenous inefficiency determinants as shown in Equation (8).

$$\begin{gathered}\mu_{it} = \phi_0 + \phi_{Int} Int_{it} + \phi_{Pat} Pat_{it} + \phi_{Size} Size_{it} + \phi_{Years} Years_{it} + \\ \phi_{Man} Man_{it} + \phi_{ST} ST_{it} + \phi_{IC} IC_{it} + \sum_{j=1}^{N} w_{ij} Int_{jt} \delta_{Int} + \sum_{j=1}^{N} w_{ij} Pat_{jt} \delta_{Pat}\end{gathered} \quad [8]$$

Specifically, we investigate how start-ups' innovative activity influences incumbent firms' efficiency level considering in the inefficiency model intangible investments and patent filling. In particular, we measure the share of investments in intangible capital as the ratio between investments in immaterial capital over total investments (*Int*). Intangible assets may be identified as a proxy for firms' innovative activity because they represent the value of a firm's information and communication technology, organizational capital, and investments in R&D (Bernini, Galli, 2022). Therefore, companies' competitiveness and success may be strongly associated with intangible investments because they allow new knowledge acquisition and process improvements (Montresor, Vezzani, 2016). Moreover, we measure start-ups' patenting activity through the dummy variable *Pat* which takes a value of 1 if the firms registered at least one patent in the time period considered and 0 otherwise. Patents are a very commonly used indicator of firms' innovative activity because patenting allows innovative start-ups to protect the newly developed product as trade secrets, granting the innovative firm a competitive advantage (Nelson, 2009). Besides considering how start-ups' internal innovation affects their efficiency level directly, we also consider spillover effects arising from innovative activity performed by neighbours. Indeed, incumbent firms may take advantage of knowledge originating from the external environment through emulation, cooperation and exchange of ideas with neighbouring firms. Therefore, we include in the model specification also the spatial lag of *Int* and *Pat* to evaluate whether investments in intangible capital performed by neighbours and having innovative firms that have registered patents as peers influence start-ups' efficiency level through knowledge spillovers.

In order to consider start-ups' heterogeneity we include in the inefficiency model also some control variables such as *Size* and *Years* where the former measures the start-ups' size as the logarithm of the number of employees and the latter captures the age of the head. Finally, we also take the three main sectors of activity into account including three dummy variables to identify those start-ups working in the manufacturing sector (*Man*), in the scientific and technological sector (*ST*), and in the information and communication sector (*IC*). We do not include the spatial lag of the control variables in the inefficiency model since the focus of the analysis is on start-ups' innovation and spillover effects arising from innovative activity performed by neighbours.

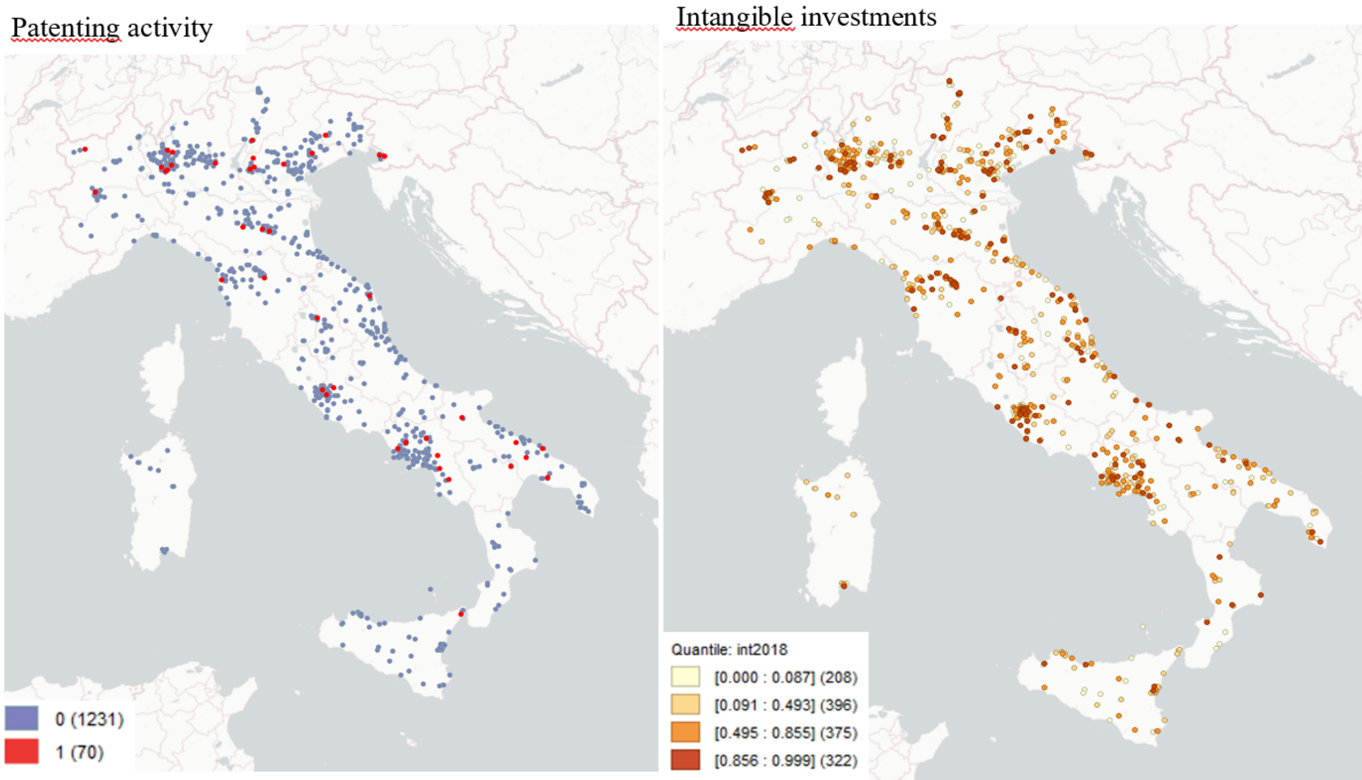
More details on the variables used in the analysis and some descriptive statistics are provided in Table 1. Moreover, some insights on the innovative activity performed by Italian start-ups can be found in Figure 1. In particular, it can be observed that only 70 firms over 1301 have developed at least one patent in the time period considered and these firms tend to be located in the main

Table 1 – Variables and Descriptive Statistics

Variables	*Definition*	*Min*	*Mean*	*Max*	*SD*
Y	Log(valueadded)	0	3.33	6.87	1.77
L	Log(totalsalaries)	0	2.04	6.81	2.02
K	Log(fixedcapital)	0	1.55	6.80	1.71
t	1 if 2018; 2 if 2019; 3 if 2020	1	2	3	0.82
Int	Share of intangible investments over total investments	0	0.48	0.99	0.37
Pat	1 if the firm has registered at least one patent in the time period; 0 otherwise	0	0.04	1	0.19
Size	Log(numberofemployees)	0	0.55	3.09	0.70
Age	Log(age)	3.13	3.81	4.44	0.25
Man	1 if in manufacturing sector; 0 otherwise	0	0.14	1	0.34
IC	1 if in information and communication sector; 0 otherwise	0	0.48	1	0.50
ST	1 if in scientific and technological sector; 0 otherwise	0	0.26	1	0.44

Source: Authors' elaboration

Figure 1 – Start-ups' Innovative Activity



Source: Authors' elaboration

Italian metropolises such as Rome, Milan, Naples, Bologna, Turin, etc. Considering start-ups' intangible investments, the right panel of Figure 1 shows that investments in intangible assets tend to prevail in firms belonging to innovative clusters rather than in firms located in isolated locations.

4. Estimation Results, Marginal Effects and Efficiency Scores

The results in Table 2 indicate that Italian innovative start-ups' are affected globally by positive and significant productivity spillovers. Indeed, the estimate

Table 2 – Estimation Results

	Coeff	*SD*
B_0	6.45 ***	0.23
B_L	0.57 ***	0.02
β_K	0.24 ***	0.01
β_t	0.05 ***	0.00
θ_L	0.02	0.04
θ_K	0.01	0.05
ρ	0.04 *	0.03
ϕ_0	5.46 ***	0.41
ϕ_{Int}	-0.45 ***	0.07
ϕ_{Pat}	-0.03	0.13
ϕ_{Age}	0.01 ***	0.00
ϕ_{Size}	0.07 **	0.06
ϕ_{Man}	0.04	0.08
ϕ_{IC}	-0.15 ***	0.08
ϕ_{ST}	-0.31 ***	0.09
δ_{Int}	-0.49 ***	0.18
δ_{Pat}	0.15	0.31
σ^2	1.42	-
λ	0.39	-
Min TE	0.01	
Mean TE	0.16	
Max TE	0.64	

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10
Source: Authors' elaboration

of ρ equals 0.04 and is significant at a 5% significance level. Therefore, having productive firms as neighbours positively affects the productivity level of peers. However, due to the introduction of the spatial lag of the dependent variable, we cannot interpret the β and the ϕ estimates in a meaningful way because they do not coincide with the first partial derivatives of Y with respect to X and Z, respectively. Thus, marginal effects have to be computed separately.

Table 3 shows the marginal effects of both the input variables and the inefficiency determinants. Starting from the direct effects related to labour and capital, we find that both inputs have a positive and significant effect on start-ups' productive performance as expected, but labour (0.57) contributes more to shaping incumbent firms' productivity level compared to capital (0.24). Indeed, in the first phases of a business, capital investments may be still limited and start-ups' competitiveness may primarily depend on labour forces. Considering the indirect effects originating from labour and capital of neighbouring producers, we find evidence of positive but non-significant input spillovers. Thus, in the early stages of a firm's activity, being located in areas with a high endowment of assets and workers may not be such influential due to the key role of internal investments.

Passing to the marginal effects of the inefficiency determinants, we find that both internal intangible investments and patenting activity contribute to decreasing firms' inefficiency level but while the former effect is highly negative in

Table 3 – Marginal Effects of the Input Variables and of the Inefficiency Determinants

Inputs:	*Direct effect*	*Indirect effect*
L	0.57 ***	0.05
K	0.24 ***	0.02
Inefficiency Determinants:		
Int	-0.45 ***	-0.52 ***
Pat	-0.03	0.16
Size	0.07 **	-
Age	0.01 **	-
Man	0.04	-
IC	-0.15 ***	-
ST	-0.31 ***	-

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10

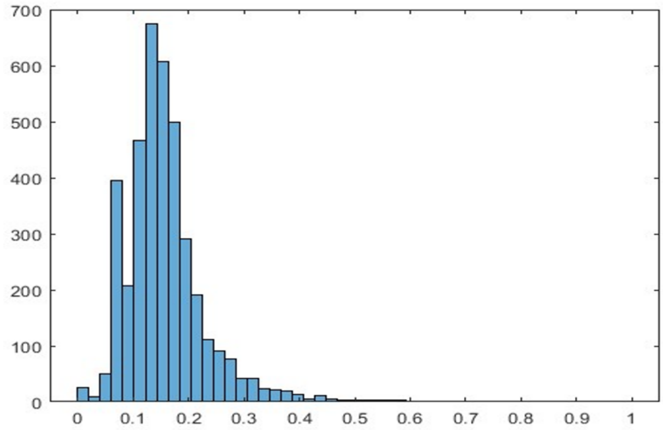
Source: Authors' elaboration

magnitude (-0.45) and significant, the direct effect related to registered patents results to be negative but non-significant (-0.03). Indeed, innovative activity performed through ICT and R&D investments can allow start-ups to develop new competitive products and services and to improve business processes and operations while patenting activity can help protect the newly developed products thanks to property rights that prevent other firms to commercialize them (Helmers, Rogers, 2011). However, the direct effect of patents may result to be non-significant since very few start-ups registered at least one patent in the years of analysis (only 4% of firms in our sample). Indeed, patenting is usually too expensive for incumbent firms (Andries, Faems, 2013; Frietsch *et al.*, 2013). Considering the indirect effects arising from neighbouring start-ups' innovative activity, we find that while positive and significant knowledge spillovers originate from intangible investments performed by peers, neighbours' registered patents have a negative indirect effect on the efficiency level of neighbouring producers even if it appears to be non-significant. Indeed, investments in ICT and R&D performed by neighbours tend to decrease the inefficiency level of peers (-0.52) while the indirect effect of patents on inefficiency results to be positive (0.16). Thus, we find evidence of positive knowledge spillovers originating from highly innovative clusters while patents registered by neighbours result to have an effective blocking function with respect to the newly developed products even if it is not statistically significant.

Finally, we find that the direct effect of size is positive (0.07) and significant and thus, bigger start-ups tend to be more inefficient than smaller ones. This insight is not uncommon in the literature since, greater firm size requires major monitoring and coordination costs (Liang *et al.*, 2008) and it can slow down managers' competitive moves and agreements on firms' strategy (Hambrick *et al.*, 1996; Iaquinto, Fredrickson, 1998) making communication, coordination, and decision making more difficult and inefficient, especially in the early stages of a business (Matricano *et al.*, 2022). Moreover, our results indicate that the age of the head positively affects inefficiency indicating that younger managers tend to run businesses more efficiently compared to elderly people. Finally, we find that while start-ups in the manufacturing sector tend to be more inefficient than others, the most efficient start-ups are those belonging to the information and communication sector (-0.31) and the scientific and technological sector (-0.15).

Considering the technical efficiency scores, the last three rows of Table 2 show some insights on the minimum, mean and maximum levels of efficiency of Italian innovative start-ups. In particular, we find that, in the time period considered, the average level of technical efficiency of Italian start-ups is very low and equal to 0.16. The histogram in the upper panel of Figure 2 confirms this finding, showing a distribution of the TE scores very concentrated around the low values, with very

Figure 2 – Technical efficiency scores



Source: Authors' elaboration

few firms reaching scores higher than 0.4. Moreover, the lower panel of Figure 2 shows some insights on the geographical distribution of the TE scores, highlighting that more efficient start-ups tend to be located in neighbouring locations in the areas of Milan, Rome, Naples, Bologna and Padua. On the other hand, less efficient start-ups are mostly located isolated in space and in the internal areas of Italy.

5. Conclusion

In this paper, we investigate the productive performance of Italian innovative start-ups in the time period 2018-2020 taking spatial effects occurring across neighbouring firms into account. In particular, we consider spillover effects influencing both firms' productivity and efficiency levels by estimating the comprehensive spatial stochastic frontier model introduced by Galli (2023) including three different kinds of spatial effects. Indeed, besides considering productivity and input spillover related to the frontier function, this model specification allows capturing the specific spatial effects arising from each inefficiency determinant and influencing start-ups' efficiency levels. Thus, considering start-ups' innovative activity as one of the main sources of (in)efficiency, we analyse both the effect of internal innovation on the efficiency level of Italian incumbent firms and whether neighbouring firms' innovative activity also contributes to boosting peers' performance. To reach this goal, we use georeferenced firm-level data from the AIDA Bureau Van Dijk database on Italian innovative start-ups in the time period 2018-2020.

The results from our analysis indicate that internal intangible investments performed by start-ups significantly contribute to reducing the level of inefficiency of firms. Moreover, also investments in intangible capital of neighbouring producers tend to positively and significantly affect start-ups located in neighbouring areas likely due to knowledge spillovers. Indeed, being embedded in highly innovative clusters positively influences all firms belonging to the cluster thanks to knowledge transfer, innovation sharing and transmission of ideas. Considering patents, we find that while they contribute to decreasing firms' inefficiency level from an internal point of view, negative spillover effects generate across neighbouring units due to their protecting and blocking function with respect to the newly developed products. However, both the direct and indirect effects of patent results to be non-significant since most of the Italian start-ups did not register any patent in the time period considered.

Findings from this paper are relevant both from a theoretical and a practical perspective. Indeed, despite the importance of knowledge spillovers for start-ups formation and survival is highly recognized in economic literature from a theoretical point of view, we provide empirical evidence on the close link between start-ups' innovative activity, neighbouring start-ups' innovation, and incumbent firms' productive performance. In designing plans and policies to support entrepreneurial activity, policymakers can therefore rely on insights from this work in order to strengthen start-ups' performance by promoting internal innovative activity as well as firms' cooperation, networking, and exchange of ideas. Therefore, in order to support and sustain Italian innovative start-ups, governments should design ad hoc policy interventions at the local level as suggested by Capello and Lenzi (2013) aiming at strengthening the linkages and collaboration between inventors, skilled people and entrepreneurs to facilitate knowledge and innovation sharing that in turn can lead to higher industrial performances and finally to increased employment and economic growth (Antonietti, Gambarotto, 2020).

In future extensions of this work, it could be interesting to run this kind of analysis for a longer time span taking into consideration start-ups entering and leaving the sample over time by using an econometric approach suited for unbalanced panel data. However, to date, there are no available methods dealing with both spatial effects and unbalanced panel data in a stochastic frontier setting.

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Effetti spaziali relativi all'attività innovativa delle start-up italiane: un approccio frontiera spaziale

Sommario

Le start-up hanno un ruolo fondamentale per la crescita economica dei paesi poiché stimolano l'inventiva e le dinamiche di mercato e in particolare, in periodi di profonde trasformazioni, diventa ancora più importante conoscere i fattori che contribuiscono alla loro sopravvivenza. Tra gli altri, l'innovazione è un elemento chiave per migliorare la performance e favorire la sopravvivenza e la competitività delle nuove imprese. Oltre a fonti di innovazione come gli investimenti interni in ricerca e sviluppo e la presenza di personale esperto e qualificato, anche l'ambiente esterno in cui si le start-up sono collocate può rappresentare una fonte importante di nuova conoscenza grazie agli effetti spaziali che si verificano all'interno dei cluster innovativi. Pertanto, in questo articolo viene analizzato l'impatto degli spillover di conoscenza sul livello di efficienza delle start-up italiane, differenziando tra gli effetti spaziali derivanti da investimenti in capitale intangibile e dall'attività brevettuale delle imprese. Inoltre, valutiamo anche se si verificano spillover di produttività e a livello di input tra start-up vicine. Per svolgere questo tipo di analisi, sono stati utilizzati dati georeferenziati a livello di impresa sulle start-up innovative italiane nel periodo 2018-2020 ed è stato stimato un modello frontiera spaziale

che consente di considerare diverse fonti di dipendenza spaziale. I risultati dell'analisi possono indirizzare i policymakers nel progettare piani e politiche volti a favorire la competitività delle start-up sfruttando l'interazione e la cooperazione tra imprese.

Part 3

Socio-Economic Transformations: The Role of Cohesion Policies

European Structural Investment Funds Multipliers in the Italian Regions

Gianluigi Coppola, Sergio Destefanis*, Mario Di Serio*, Matteo Fragetta**

Abstract

In a period of worsening of regional disparities due to the deep transformations European economies are going through (digitalisation, globalisation, pandemic, and political crises), it becomes extremely vital to measure the multiplier effects of European Structural Investment Funds (ESIFs) on local economies. For this reason, this paper estimates the multipliers of ESIFs in eighteen Italian administrative regions throughout 1994–2016. We innovate vis-à-vis previous work by providing well-behaved region-specific multipliers and by studying in detail the dynamic behaviour of ESIFs, as well as the factors driving the determination of multipliers across regions. We find substitutability between ESIFs and other public expenditure variables, which runs counter to the principle of additionality of the EU cohesion policy. A cross-region analysis of multipliers suggests that their values are positively associated with labour slack as well as with technological capability.

1. Introduction

There are profound territorial economic inequalities today in the European Union (EU), which have been worsened by far-reaching changes in the global economy (digitalisation, various waves of globalisation, disruptions of the chain of value due to pandemic and war). As a primary tool to sustain regional development and to fight these inequalities, the EU created and strengthened the European Structural and Investment Funds (henceforward, the ESIFs). Due to its relatively high GDP per capita, Italy never qualified for the EU's Cohesion Fund. On the other hand, in Italy the ESIFs historically comprised (a) the European Regional Development Fund (ERDF), created to reduce regional imbalances; (b) the European Social Fund (ESF), which promotes active labour market policies; (c) the European Agricultural Guidance and Guarantee Fund (EAGGF), aimed at the adjustment of agricultural structures and the development of rural areas

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by substituting; and (d) the Financial Instrument for Fisheries Guidance (FIFG) that supported the national fishery programmes. In 2007, the EAGGF was substituted by the European Agricultural Fund for Rural Development (EAFRD) and the European Agricultural Guarantee Fund (EAGF), and the FIFG was substituted by the European Fisheries Fund (EFF). Strictly speaking, the EAFRD, EAGF and EFF are no longer classified as ESIFs. However, we include them in our empirical analysis along with the ERDF and the ESF, in continuity with the praxis adopted for the EAGGF and the FIFG. In practical terms, all these funds still belong the *Fondo di Rotazione per le Politiche Comunitarie*, the revolving fund through which these funds are disbursed to the regions.

A very fierce debate still rages on the persistence of territorial differences in Italy, between the Centre-North and the Mezzogiorno,[1] and on the effects of ESIFs on these gaps. The two issues are closely connected, because after the end of the extraordinary intervention in the South in 1992, ESIFs represents the main tool, if not the only one, for reducing these gaps. Italian dualism, measured in terms of GDP per capita, has been characterized in the last quarter of a century by a different dynamic of its components: GDP per employee, which is a measure of labour productivity, and the employment rate (data the ratio of employed persons to population). The data show (see, e. g., Svimez, 2019, p. 52) that from 1995 to 2018 between the Centre-North and the South and Islands the gap in terms of GDP per capita increased slightly, while the gap in labour productivity decreased equally slightly. Both variations were stronger in the periods preceding the economic crisis. On the other hand, the employment rate differential steadily increased throughout 1995-2018. The question remains open whether this evolution can be at least partially ascribed to a different effectiveness of cohesion policies over time.

In this paper, relying on the empirical procedure developed in Destefanis *et al*. (2022), we proceed to the computation and analysis of fiscal multipliers for ESIFs. Unlike in Destefanis *et al*. (2022), we focus on eighteen Italian regions, excluding Valle D'Aosta and Molise from the analysis. We do so because of the erratic values typically obtained for the multipliers of these very small regions. If the analysis is restricted to the other eighteen regions, the analysis of the factors presiding to the determination of regional multipliers can rely on traditional regression techniques and thus yield novel insights with respect to the exploratory analysis carried out in Destefanis *et al*. (2022). Relative to previous work, we also proceed to a deeper assessment of the conformity of ESIFs and other public expenditure variables to the principle of additionality of the EU Cohesion Policy, according to which EU

1. The Mezzogiorno includes the southern regions (Abruzzo, Molise, Campania, Puglia, Basilicata, and Calabria) and the isles (Sicilia and Sardegna).

resources should be additional – and not a substitute – to other national and/or regional funding sources (EU Regulations 4253-4256/1988).

Our paper connects with the study of the effects of fiscal policy, which has regained prominence in the economic debate. Much of the recent literature has focused on subnational analyses of fiscal policies because of the advantages to be obtained in terms of identification of fiscal shocks. Indeed, subnational bodies, such as states in the US or regions in European countries, are subjected to fiscal and monetary policies that are relatively unresponsive to their idiosyncratic conditions facilitating the computation of fiscal multipliers based on exogenous shocks.[2]

As already noted above, Italy is a particularly interesting case study for region-specific policies because of the existence of an area of the country, the Mezzogiorno, whose delays in development are relevant and have been perpetuated over time. We produce region-specific multipliers estimating a random effect panel vector autoregressive model through Bayesian techniques from 1994 to 2016. The variables taken into consideration for the estimation of the model are ESIFs, nationally funded government investment, government consumption, gross fixed capital formation, and GDP.

The rest of the paper has the following structure. In section 2 we survey the literature about the effectiveness of ESIFs across the Italian economy. Section 3 describes the econometric specification and the data used. Section 4 is dedicated to the discussion of the results. Section 5 concludes the paper.

2. The Literature

In this survey we will consider some works that focus on Italian territorial units, and on the effects of EU cohesion policies on GDP per capita and its components. We will focus first on some analyses carried out on regional aggregate data.

One of the first studies that takes into consideration the cohesion policy in the Italian regions is Percoco (2005) A supply side model à De la Fuente (2002) is estimated for six regions of the Mezzogiorno throughout the programming period 1994-1999. A GMM estimator is applied to a Cobb-Douglas function with GDP as dependent variable and private capital, social and economic infrastructure, employment, and human capital as regressors. The effects of ESIFs on GDP are imputed through the weight that their spending has on these regressors. The evidence points to overall positive, but heterogenous, effects across regions.

Coppola and Destefanis (2015, 2007) consider all Italian regions from 1989 to 2006 and use a non-parametric procedure to decompose the evolution of GDP

2. A thorough analysis of the literature based on the application of time series techniques to subnational data, focusing on US studies, is provided in Chodorow-Reich (2019). Destefanis *et al*. (2022) also describe the relatively few studies of this kind carried out on non-US data.

per capita into various elements. Through regression analysis they measure the impact of ESIFs on each of these elements. They find a positive impact of ESIFs, which however dwindles toward the end of period for capital deepening and employment.

Aiello and Pupo (2009) estimate a neoclassical convergence model augmented by the amount of ESIFs for all regions from 1996 to 2007. They find a weak impact of ESIFs (greater in Southern regions) on GDP per capita, while, in contrast to previous works, they find no effect on labour productivity.

Barone *et al*. (2016) apply a counterfactual analysis aimed at demonstrating that ESIFs produce effects only in the short term. They take into consideration the dynamics of the GDP per capita of Abruzzo. This region was part, with all the other Mezzogiorno regions, of the Convergence Objective 1 only until 1996. For this reason, Abruzzo no longer benefited from EU convergence funds after 2000. The authors find that, after this date, the GDP per capita of Abruzzo has not grown as in the previous period, and they interpret this result as evidence that ESIFs have not activated a process of endogenous growth.

Coppola *et al*. (2020) use data from the *Ragioneria Generale dello Stato* to analyse the impact of both ESIFs and nationally funded regional development policies on the GDP per capita of the twenty Italian regions from 1994 to 2013. In a counterfactual framework of, the authors apply a control function approach. They also consider the impact of the regional socio-economic context on policy effects. They find a positive impact of ESIFs, and, for nationally funded policies, only a relatively minor impact for current account subsidies to enterprises. The governance capacity of the regions has an impact only for the latter funds.

Arbolino *et al*. (2020) analyse the short-term of EU Cohesion Policy on regional labour markets throughout the 2007-2013 period. They find that this policy, has positive effects of an anti-cyclical nature. Its effects are also positively conditioned by quality of regional institutions.

Destefanis *et al*. (2022), using a Bayesian VAR model, estimate the multipliers of different types of public expenditure in the 20 Italian administrative regions in the period 1994-2016. The results show that ESIFs, compared to other types of public expenditure, provide the highest multipliers. An exploratory analysis of the distribution of multipliers across regions and spending types suggests that regional multiplier values are positively associated with labour slack and region size.

There is also a body of works evaluating the impact of ESIFs on sub-regional or firm-level data. Ciani and De Blasio (2015) estimate the impact of ESIFs on employment, population, and property prices in the Local Labour Systems of Southern Italy for the period 2007-2013. They find a somewhat limited impact of ESIFs. Albanese *et al*. (2019) measure at the firm level (the data relate to firms in the South for the period 2007-2015) the impact of the European Regional

Development Fund on total factor productivity. Their evidence points to the lack of effectiveness of the European Regional Development Fund, except for the funds spent on infrastructure.

Yet other works apply the Regression Discontinuity Design method, considering as geographical discontinuity the administrative borders between the areas belonging to the regions under the Convergence Objective of the EU Cohesion Policy and the neighbouring areas included in other regions.

In Giua (2017), where the outcome variable is the change in employment (based on census data) between 1991 and 2001, European regional policy has a positive effect on the dynamics of employment and there is no crowding-out effect on employment in other regions. The impact is particularly positive for some key sectors (industry, construction, retail trade, tourism). However, in a more recent article, Crescenzi and Giua (2020) find that the positive employment effects of belonging to the Convergence Objective regions were no longer present in Italy during the Great Recession. Albanese *et al*. (2021) present estimates of the effectiveness of ESIFs on some indicators of regional well-being, including educational, health and demographic outcomes, for period 2007-2013. They find a modest impact of the policy on youth employment, female activity rate and tertiary education. Furthermore, they argue that the quality of institutions, human capital and urban density only affect the ability of the policy to have significant effects on GDP and employment. Cerqua and Pellegrini (2022) estimate the impact of all public local development projects for the 2007-2015 period. The effects are close to zero for local income (data from MEF source) and positive for the number of local units and their employees (data from ASIA source).

Clearly, the empirical studies on the effects of the EU Cohesion Policy in Italy do not yield univocal results. Papers can be divided among those that find ESIFs as virtually ineffective, those that find the opposite result, and a third category where a positive impact is conditioned on some factors. The last point is further developed in Fratesi (2020), Fratesi and Perucca (2016, 2019), Pellegrini and Tortorella (2018; see p. 8). Other systematic reasons for the different results may depend, for all variables, (a) on a varying effectiveness of policy over time; (b) on the dynamic modelling of the expenditure data. Below we deal with both these points.[3]

We aim to shed novel light on the debate about the ESIF effectiveness, by analysing the dynamic multipliers of ESIFs on GDP throughout a rather long period (1994-2016), covering four ESIF programming periods. We innovate

3. As far as employment is concerned, one should also consider (a) the complexity of the dynamic links between GDP and employment, which was already highlighted by Percoco (2005); (b) the fact that employment support is mainly carried out through the ESF, whose governance differs from that of the other ESIFs (for example in terms of greater fragmentation of projects). We aim to deal with these points in future research.

vis-à-vis previous work by providing well-behaved region-specific multipliers and by studying in detail the dynamic behaviour of ESIFs. More in detail, we analyse the relations of complementarity or substitutability among ESIFs and other public expenditure variables, to assess whether they conform to the principle of additionality of the EU cohesion policy. Our empirical procedure yields multipliers differentiated across regions, which calls for an analysis of the determination of their differences. Accordingly, we develop upon the analysis of Destefanis *et al*. (2022), by studying the factors driving the determination of cross-region multipliers in a multivariate framework that yields novel insights.

3. The Empirical Framework

We rely on the Bayesian random effect panel vector autoregressive model suggested in Canova and Ciccarelli (2013). Coefficients of our panel vector autoregressive (PVAR) model can vary across regions, although they derive from a distribution with a similar mean and variance. We avoid potential overfitting problems by implementing a Bayesian estimation method. More specifically, we consider a PVAR model with cross-subsectional heterogeneity, obtaining a unit-specific vector autoregressive (VAR) model by means of a random coefficient model. For each region, the VAR model is

$$y_{it} = \Gamma_i z_i + A_1^1 y_{i,t-1}, + ... + A_i^p y_{i,t-p} + \varepsilon_{i,t} \quad [1]$$

with

$$\varepsilon_{i,t} \sim N(0, \Sigma_i) \quad [2]$$

where t=1,…,T denotes the time dimension; i=1,…,N denotes the region dimension; $y_{i,t}$ is an n×1 vector of endogenous variables; z_i collects deterministic components; A_i and Γ_i are matrices containing the slope and intercepts; and p is the number of lags.

We estimate the model described in equation (1) for the eighteen regions in our sample, using annual data from 1994 to 2016. As already explained in the Introduction, we exclude Valle D'Aosta and Molise from the estimation sample with a view to avoid erratic multiplier values. Our vector Y of endogenous variables is

$$Y_{i,t} = \left[GC_{i,t}, GI_{i,t}, RF_{i,t+1}, I_{i,t}, GDP_{i,t} \right] \quad [3]$$

where *GC, GI RF, I,* and *GDP* represent nationally funded government investment (*GI*), government consumption (*GC*), revolving fund (our measure of *ESIFs*) (*RF*), gross fixed capital formation (*I*), and GDP, respectively. To control for country-level factors, we also include year fixed effects in our panel model.

Government consumption, gross fixed capital formation, and GDP are downloaded from the I.Stat database of the Italian Statistical Office (ISTAT), whereas nationally funded government investment and the revolving fund, through which the Italian government distributes the *ESIFs* to the regions, are taken from the database *Spesa statale regionalizzata* of the General Accounting Office (*Ragioneria Generale dello Stato*) at the Italian Ministry of Economy and Finance, the only source that allows one to distinguish between these two kinds of public expenditure. The revolving fund also includes the so-called national cofinancing that, in Italy, covers up to 50% of total project costs. All variables are at constant (2010) prices.

A substantial proportion of nationally funded government investment and revolving fund is not allocated to any single region, but to multiregional aggregates. In the following analysis, we assume that these funds are spread across regions proportionally to the shares of regionally allocated funds. This is the hypothesis most often maintained in the literature (see Coppola *et al*., 2020) as making sense from an a priori standpoint. Also following Coppola *et al*. (2020), as well as Destefanis *et al*. (2022), we include in our model the RF variable forwarded by one year. Indeed, ESIFs are paid out to the regions with a lag of approximately one year with respect to the regions' spending decisions. This effectively means that the revolving fund expenditures written down for year t have already been spent in year *t*-1.[4]

To implement a parsimonious model and avoid problems of over-parameterisation, we estimate our *PVAR* model with a lag structure of 1 year (*p*=1). Structural shocks are recovered from estimated residuals applying the Cholesky identification scheme, which transforms Σ_i to a lower triangular matrix. The application of this scheme imposes a causal ordering on the endogenous variables: we suppose that a shock to a specific variable of our *PVAR* affects previously ordered variables with a lag and following variables contemporaneously. In our case, we assume that a shock to public expenditure affects GDP contemporaneously but that a shock to the latter affects public expenditure with a lag. This identification strategy is very common in the *VAR* research on government spending shocks also when annual data are used (see, e.g., Pereira, Roca-Sagales, 1999; Kamps, 2005; Di Giacinto *et al*., 2010; Pereira, de Fatima-Pinho, 2011; Deleidi *et al*., 2020, Destefanis *et al*., 2022). As already noted, the short-term inertia of public expenditure is likely to be even particularly pronounced in the case of NUTS2 regions, which are subjected to policies relatively unresponsive to their idiosyncratic conditions.

4. This time pattern between the EC payments to the member states and the dates on which expenditures take place on the ground is also noted in EU Commission (2018), which provides a measure of the 'expenditures taking place on the ground' closely following the evolution over time of our forwarded RF. The EU Commission's measure, however, does not include national cofinancing and is available for fewer years than our RF.

With respect to the ordering of fiscal variables, we consider government consumption as the 'truly exogenous' variable. Hence, nationally funded government investment and the revolving fund are assumed to react contemporaneously to a government consumption shock. On the other hand, government consumption reacts with a lag to shocks on nationally funded government investment, whereas government consumption and nationally funded government investment react with a lag to shocks on the revolving fund. Therefore, the ordering of variables of interest is as follows: (1) government consumption, (2) nationally funded government investment, (3) the revolving fund, (4) gross fixed capital formation, (5) GDP. In section 4 we also report the results obtained with an alternative identification scheme.

Once we have identified shocks for RF, government consumption, and nationally funded government investment, for each draw from the posterior, we derive impulse response functions for a time horizon of 10 years. Then, we compute the median response across the 10,000 draws and save the 16th and 84th percentile of their distribution as confidence bands.

Regarding the computation of multipliers, we follow the approach of Gordon and Krenn (2010) and Ramey and Zubairy (2018). They argue that the common method of transforming variables in logarithms can lead to biased estimates of multipliers. It implies an ex-post conversion from elasticities that is based on a factor representing the sample average of the ratios between the fiscal variable and GDP. This ratio may vary widely over time, and the resulting multipliers may not be representative of any period in the sample. Conversely, relating the fiscal variable and GDP to the potential GDP enables us to compute multipliers directly without the need to make any ex-post conversion. Thus, having normalised the fiscal variables by real potential GDP, we compute multipliers directly using the following formula:

$$M_H = \frac{\Sigma_{h=0}^{H} dGDP(h)}{\Sigma_{h=0}^{H} dG(h)} \qquad [4]$$

where h=0,1,…H represents the time horizon over which the multiplier is computed, $\Sigma_{h=0}^{H} dGDP(h)$ is the discrete approximation of the integral of the median impulse response function (IRF), and $\Sigma_{h=0}^{H} dG(h)$ is the discrete approximation of the integral of the median IRF of the considered public expenditure aggregate. Our baseline measure of real potential GDP is obtained using the Hodrick and Prescott (1997) filter on regional GDP data.

4. The Results

Figures 1a – 1b show the impulse responses deriving from a shock to RF. For virtually all regions of southern Italy, as well as for some other regions,

Figure 1a: Impulse Responses to Revolving Fund shock for Piemonte, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Liguria, Emilia-Romagna, Toscana, Umbria, Marche. The red shaded area represent the 16th and 84th credible interval. The blue solid line represent the median response

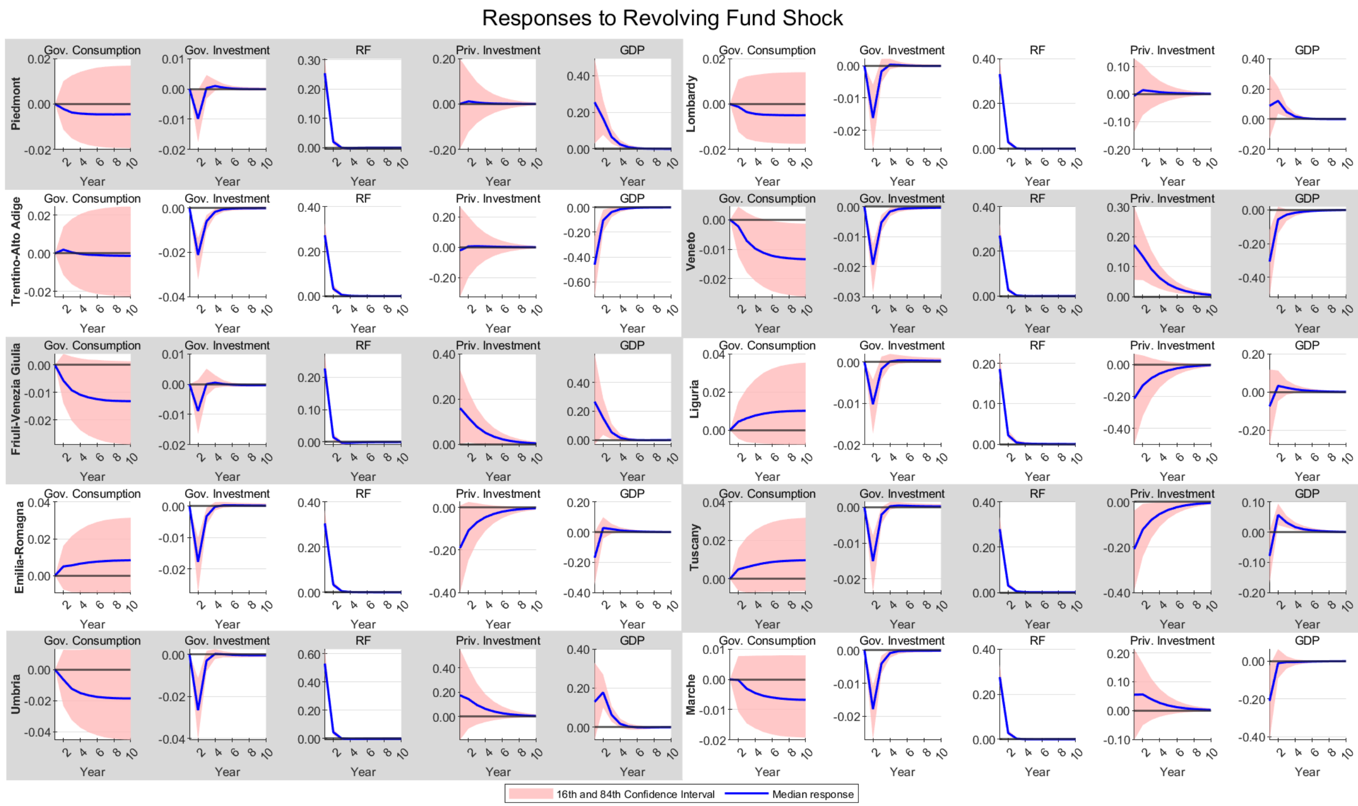
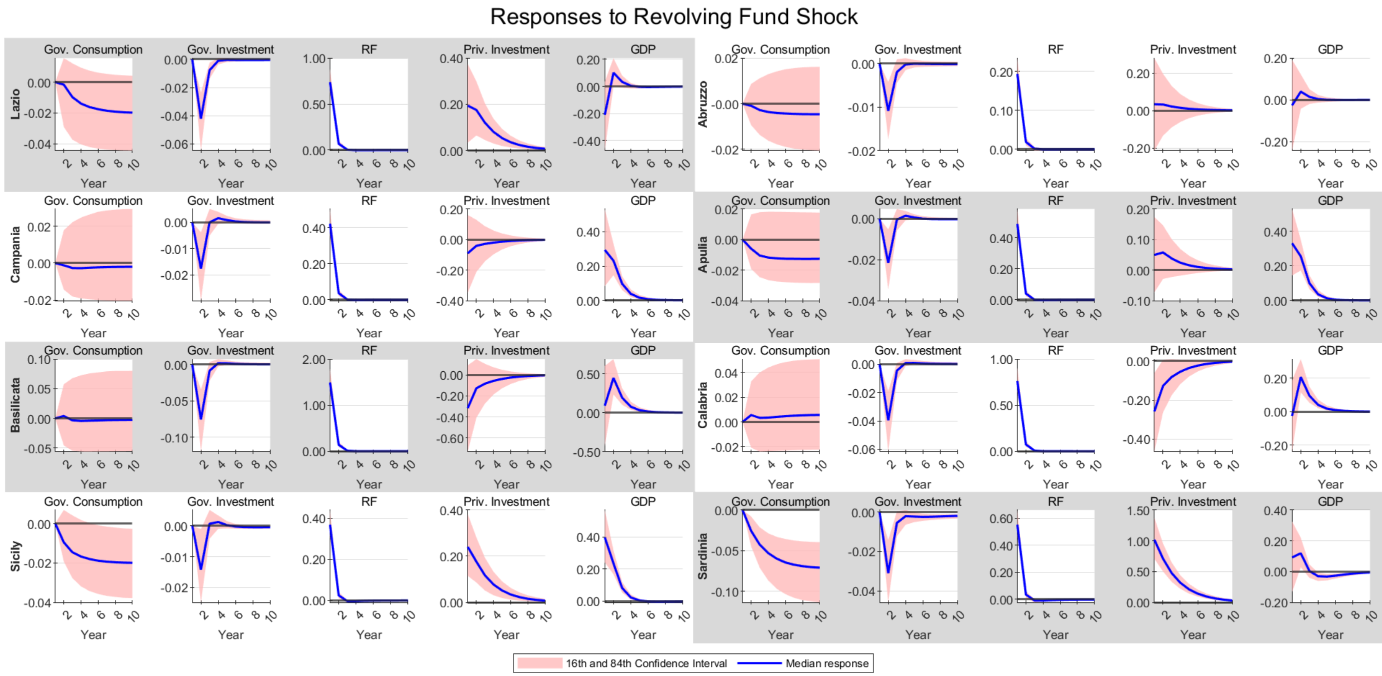


Figure 1b: Impulse Responses to Revolving Fund shock for Lazio, Abruzzo, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna. The red shaded area represent the 16th and 84th credible interval. The blue solid line represent the median response



Source: Authors' elaboration

GDP reacts quite strongly and significantly. On the other hand, for Trentino-Alto Adige, Veneto, Liguria, Marche, and Abruzzo (the only southern region in this list), the response of GDP is zero or barely above zero. These results could reflect the response of nationally funded government investment and government consumption to an RF shock. The former reacts negatively and significantly for all regions except Piemonte, Lombardia, Liguria, Friuli-Venezia Giulia, Campania, Puglia, and Sicilia, where responses are mostly negative but not significant. Government consumption reacts negatively but not significantly for all the regions. This behaviour suggests a fair degree of substitutability between RF and other expenditure variables, squarely contradicting the EU Cohesion Policy's principle of additionality. Interestingly, gross fixed capital formation reacts positively in most regions, and sometimes significantly, to an RF shock, highlighting that a shock to RF implies a slight crowding-in effect on gross fixed capital formation.

Table 1 shows the RF multipliers for each region. They are computed using equation (4) for horizons of one, three, and five years. Multipliers derived from impulse responses that are significantly different from zero are highlighted in bold.

As is customary in this literature, we also produced multipliers swapping the orderings of the public expenditure aggregates in the Cholesky identification scheme, obtaining evidence qualitatively very similar to the baseline findings. The option also exists, of course, to rely on a completely different identification scheme. As a robustness check, we produced multipliers based on the Generalised Impulse Response Function (GIRF) approach developed by Koop *et al.* (1996), which provides multipliers that are not affected by the reordering of the vector of endogenous variables. As a further robustness check, to compute multipliers we divide all fiscal variables by an estimate of potential GDP, based on a cubic trend filter, like in Ramey and Zubairy (2018). In Table 1 we report results from these two robustness checks, as well as from the baseline case.

Multiplier values are clearly in the neighbourhood of the previous studies reviewed in section 2. However, they vary widely across regions, clearly replicating the patterns we have already discussed for the impulse responses. Interestingly, the results for our baseline case are, so to speak, a median case between those from the GIRF approach (generally yielding lower multipliers) and those relying on a potential output computed with a cubic trend (generally yielding higher multipliers). At any rate, the marked heterogeneity of multipliers across areas warrants further discussion. The Mezzogiorno multipliers are tendentially larger than those for the rest of the country. These findings have obvious implications for the setup of policies aimed at reducing territorial inequalities in Italy.

Fratesi and Perucca (2016, 2019) suggest various reasons why the effectiveness of ESIFs across regions can depend on their factor and technological

Table 1 – Baseline and robustness check multipliers for a shock to RF. Multipliers deriving from significantly different from zero impulse responses are in bold

	Baseline Case			*Robustness Check # 1, Generalised Impulse Response Functions*			*Robustness Check # 2, Potential Output Computed with Cubic Trend*		
	1 year	*3 year*	*5 year*	*1 year*	*3 year*	*5 year*	*1 year*	*3 year*	*5 year*
Piemonte	**1,00**	**1,77**	**1,91**	0,54	**0,96**	1,02	**1,45**	**3,16**	**3,90**
Lombardia	0,27	**0,71**	**0,78**	0,48	**0,92**	0,99	**0,54**	**1,52**	**1,93**
Trentino-Alto Adige	**-1,69**	**-1,94**	-2,00	**-1,20**	-1,34	-1,43	**-1,71**	-2,53	-2,90
Veneto	**-1,13**	-1,31	-1,42	**-1,32**	-1,51	-1,64	**-1,25**	-1,87	-2,28
Friuli-Venezia Giulia	1,17	**1,98**	2,09	0,95	1,37	1,35	1,23	**2,70**	3,27
Liguria	-0,41	-0,10	0,01	0,15	0,52	0,61	-1,11	-1,17	-1,07
Emilia-Romagna	-0,56	-0,35	-0,30	**-0,79**	-0,63	-0,56	-0,42	-0,10	0,06
Toscana	-0,28	**0,03**	**0,11**	-0,33	**-0,04**	**0,05**	-0,15	**0,38**	**0,66**
Umbria	0,24	**0,64**	0,68	0,19	**0,54**	**0,58**	0,21	**0,85**	**1,07**
Marche	-0,76	-0,74	-0,77	-0,83	-0,79	-0,83	-0,21	0,09	0,14
Lazio	-0,28	-0,09	-0,09	-0,28	-0,12	-0,13	-0,07	0,34	0,44
Abruzzo	-0,14	0,13	0,15	**1,60**	**3,56**	**3,60**	0,25	0,88	1,06
Campania	**0,70**	**1,36**	**1,48**	0,59	**1,04**	**1,08**	**0,62**	**1,68**	**2,14**
Puglia	**0,67**	**1,29**	**1,39**	**0,47**	**0,94**	**1,02**	**0,90**	**2,16**	**2,68**
Basilicata	0,06	**0,45**	**0,51**	0,17	**0,52**	**0,56**	0,16	**0,88**	**1,20**
Calabria	-0,03	**0,33**	**0,40**	-0,09	**0,20**	**0,24**	-0,08	**0,44**	**0,68**
Sicilia	**1,08**	**1,85**	**1,96**	**0,75**	**1,33**	**1,42**	**1,29**	**2,80**	**3,38**
Sardegna	0,17	**0,37**	0,27	0,05	0,09	**-0,12**	**0,47**	**1,09**	1,12

Source: Authors' elaboration on data from "Spesa statale regionalizzata" and ISTAT endowment. Furthermore, Mineshima *et al*. (2015) list various country-specific characteristics that affect the size of fiscal expenditure multipliers in developed countries: trade openness, size of the economy, size of the automatic stabilisers, level of activity (linked to labour slack), level of public debt, financial market development, monetary policy stance, and exchange rate regime. The first four characteristics correspond almost exactly to the factors selected in Biagi and Faggian (2003) as determinants of Keynesian multipliers in a regional setup. On the other hand, level of public debt, monetary policy stance and exchange rate regime are not relevant factors across Italian regions.

From available data sources, we can elaborate some regional indicators for (a) labour-market, macroeconomic and demographic indicators: labour slack, such as the rates of unemployment and employment, size of automatic stabilisers, such as the propensity to save or GDP per capita, size of the economy; (b) external trade indicators (net imports on GDP, openness, penetration); (c) three pillars from the EU Regional Competitiveness Index (about the RCI, see Annoni and Kozovska, 2010): the Basic pillar relating to quality of institutions, macroeconomic stability, health, basic education; the Efficiency pillar measuring higher education, labour market efficiency, market size; the Innovation pillar related to technological readiness, business sophistication, innovation; (d) private and public governance: and index of civic sense calculated by Il Sole 24 Ore, 8th September 1997 (see Coppola *et al*., 2020, for further details) and the EQI from Charron *et al*. (2014); (e) financial market development; (f) technological capability, as measured by R&D expenditures, and by an index of technological potential for 1991 (from Netti, Sarno, 1998; see Coppola *et al*., 2020, for further details); (g) infrastructure endowment (taken from Bracalente *et al*., 2006); (h) sectoral structure of the economy (the share of Pavitt sectors # 1 is the share of science-based sectors over GDP, while share of Pavitt sectors # 2 sums up science-based and specialised suppliers sectors. We rely on the revised Pavitt sectoral taxonomy proposed in Bogliacino and Pianta, 2010).

In Table 2, we provide an exploratory analysis of the relationships between our baseline (five-year-horizon) ESIF multipliers and a set of their potential determinants. Excluding Valle D'Aosta and Molise from the sample yields multipliers that are normally distributed, as all the other variables of interest (diagnostics are available upon request). Hence, we proceed to our exploratory analysis through ordinary least squares. In commenting the evidence, we focus on the size of the coefficient of determination (the R^2) and on the sign of the relationship found between multipliers and their potential determinants.

Table 2 highlights a significant correlation between the size of multipliers and labour slack. RF multipliers are positively related to the rate of unemployment and negatively related to the rate of employment. We also find (generally less

Table 2 – Five-Year Baseline RF Multipliers and their Relationships with a Set of Potential Determinants

Labour-market. Macroeconomic and Demographic Factors

Variable	*Rate of unemployment*	*Rate of employment*	*Propensity to save*	*GDP per capita*	*Ln (GDP)*	*Ln (population)*	*Ln (population density)*
coefficient	0.1153	-0.0552	-0.0301	-0.0624	0.134	0.3559	-0.0637
t-ratio	2.49	-2.29	-0.90	-1.73	0.52	1.03	-0.90
R^2	0.2542	0.2207	0.0341	0.1554	0.0104	0.0617	0.0097

External Trade, EU RCI Pillars

Variable	*Total Net Imports/ GDP*	*(Foreign Exp. + Foreign Imp.)/GDP*	*Foreign Imp./GDP*	*Basic pillar (EU RCI)*	*Efficiency pillar (EU RCI)*	*Innovation pillar (EU RCI)*
coefficient	0.0095	-0.9409	-1.1639	0.1004	-0.0245	-0.0111
t-ratio	0.64	-0.56	-0.36	1.26	-1.50	-0.69
R^2	0.0137	0.0173	0.0054	0.1041	0.0742	0.0151

Governance, Financial Market Development

Variable	*EQI*	*Civic sense*	*Bank branches*		*Bank loans*	
			/GDP	*per capita*	*/GDP*	*per capita*
coefficient	-0.6836	-0.0282	-137.7211	-3.5032	-0.0145	-0.0579
t-ratio	-1.49	-1.60	-1.69	-2.60	-1.41	-1.63
R^2	0.1682	0.1841	0.1473	0.2549	0.0243	0.0626

Technological Capability, Infrastructure

Variable	*R&D expenditures*		*Technological potential*	*Infrastructure Endowment*		
	/ GDP	*per capita*		*(core)*	*(non-core)*	*(total)*
coefficient	1.3967	0.0218	0.0025	-0.0101	-0.0222	-0.0171
t-ratio	1.20	0.77	0.78	-1.65	-1.61	-2.19
R^2	0.0944	0.0319	0.024	0.0794	0.101	0.1658

Sectoral Composition

Variable	*Share of Pavitt sectors*		*Share of agriculture*	*Share of manufacturing*	*Share of services*
	#1	*#2*			
coefficient	0.0469	0.0547	-0.0185	-0.022	0.0391
t-ratio	0.81	0.89	-0.09	-0.59	0.93
R^2	0.0243	0.0347	0.0004	0.0168	0.0375

Notes: Determinants for the year 1994, except (a) EU RCI and EQI indicators; shares of Pavitt sectors, from the earliest available values, 2010 and 1995, respectively; (b) civic sense, technological potential, and infrastructure endowment, available only for 1996, 1991, and 1987, respectively.

Source: Authors' elaboration

significant) negative relationships between the multiplier size and some indicators related to the stage of development of a region (GDP per capita, EQI, Civic sense, Bank branches per capita or on GDP, Infrastructure endowment). These relationships can be rationalised in terms of the depressing impact on multipliers of the propensity to save via Engel's Law (see Biagi, Faggian, 2003), or of the lower marginal productivity of capital associated to higher stages of development (see, e. g., Coenen *et al*., 2012).

On the other hand, it could be argued that these determinants act upon the determination of multipliers in a complex way, which may not be adequately captured by simple bivariate correlations. Accordingly, we take advantage from the efficiency properties of ordinary least squares and, unlike in Destefanis *et al*. (2022), proceed to a more articulate analysis of the relationships between multipliers and their potential determinants. From the perusal of Table 2, it seems that labour slack is a particularly significant influence on RF multipliers. Hence, in Table 3 we provide evidence from a set of estimates where regressors include the rate of unemployment and all other potential determinants taken one by one. We immediately add that very similar results (available upon request) are obtained if the rate of employment is used instead of the rate of unemployment.[5]

Table 3 confirms the positive association between the size of multipliers and the rate of unemployment. This more articulate analysis also highlights however a significantly positive role for R&D expenditures (either per capita or as a share of GDP), the share of high-tech sectors over GDP, and the indicator of technological potential. It thus seems that, when controlling for labour slack, various indicators of the presence of hi-tech industries are positively correlated with the size of multipliers. The importance of the completeness of the regional economy is also suggested by the high R^2 attained when net imports over GDP are included in the regression. Unfortunately, more sophisticated indicators of completeness for the regional economies based on input-output matrixes are not readily available. We stress once more that much the same results are reached when substituting the rate of employment to the rate of unemployment.

5. Concluding Remarks

This paper contributes to a recent line of research focusing on the estimation of government spending multipliers at the local level. We use a Bayesian

5. From Table 2, one could infer that bank branches per capita are another very significant influence on the size of multipliers. Yet, if an analogue of Table 3 is constructed by substituting bank branches per capita to the rate of unemployment, one gets very poor results in terms of R^2 vis-à-vis those characterising Table 3 (results available upon request). This proves in our opinion that the relationship between bank branches per capita and size of multipliers is much more spurious than that between the latter and indicators of labour slack.

Table 3 – Five-Year Baseline RF Multipliers and their Relationships with a Set of Potential Determinants, controlling for the rate of unemployment

Macroeconomic and demographic factors						
Variable	*Rate of un-employment*	*Propensity to save*	*GDP per capita*	*Ln (GDP)*	*Ln (population)*	*Ln (population density)*
coefficient	0.2095	0.0863				
t-ratio	3.00	1.74				
coefficient	0.23		0.0856			
t-ratio	2.94		1.44			
coefficient	0.1233			0.2596		
t-ratio	2.61			1.00		
coefficient	0.1097				0.2645	
t-ratio	2.53				0.90	
coefficient	0.1175					0.0241
t-ratio	2.3					0.33
R2		0.3642	0.2942	0.2921	0.2876	0.2555

External trade, EU RCI pillars							
Variable	*Rate of un-employment*	*Total Net Imports/ GDP*	*(Foreign Exp. + Foreign Imp.)/ GDP*	*Foreign Imp./ GDP*	*Basic pillar (EU RCI)*	*Efficiency pillar (EU RCI)*	*Innovation pillar (EU RCI)*
coefficient	0.2227	-0.0505					
t-ratio	4.04	-2.52					
coefficient	0.2141		4.0986				
t-ratio	3.45		1.98				
coefficient	0.1534			4.7475			
t-ratio	2.74			1.44			
coefficient	0.1132				0.0959		
t-ratio	2.76				1.80		
coefficient	0.1947					0.0382	
t-ratio	2.24					1.26	
coefficient	0.2049						0.0481
t-ratio	2.97						1.79
coefficient	0.1892						
t-ratio	2.64						
R2		0.4182	0.3965	0.3162	0.3491	0.3137	0.3861

(...continue...)

(...continue...)

Governance, Financial market development

Variable	*Rate of unemployment*	*EQI*	*Civic sense*	*Bank branches /GDP*	*Bank branches per capita*	*Bank loans /GDP*	*Bank loans per capita*
coefficient	0.1797	0.5134					
t-ratio	1.24	0.38					
coefficient	0.1126		-0.0009				
t-ratio	1.77		-0.03				
coefficient	0.0952			-74.0869			
t-ratio	1.93			-0.84			
coefficient	0.0628				-1.9334		
t-ratio	0.75				-0.67		
coefficient	0.117					0.002	
t-ratio	2.17					0.12	
coefficient	0.1231						0.0138
t-ratio	2.01						0.26
R2		0.2698	0.2542	0.2891	0.2792	0.2546	0.2565

Technological capability, infrastructure

Variable	*Rate of unemployment*	*R&D expenditures / GDP*	*R&D expenditures per capita*	*Techno-logical potential*	*Infrastructure Endowment (core)*	*Infrastructure Endowment (non-core)*	*Infrastructure Endowment (total)*
coefficient	0.1406	2.0739					
t-ratio	3.5	1.61					
coefficient	0.1667		0.0614				
t-ratio	3.46		1.64				
coefficient	0.1769			0.0088			
t-ratio	3.44			4.14			
coefficient	0.1814				0.0063		
t-ratio	4.43				0.69		
coefficient	0.1659					0.0097	
t-ratio	3.78					0.47	
coefficient	0.1891						0.008
t-ratio	4.16						0.54
R2		0.4501	0.4576	0.4739	0.2688	0.2626	0.2619

(...continue...)

(...continue...)

Table 3 – Five-Year Baseline RF Multipliers and their Relationships with a Set of Potential Determinants, Controlling for the Rate of Unemployment

		Sectoral composition				
Variable	Rate of unemployment	Share of Pavitt sectors #1	#2	Share of agriculture	manufacturing	services
coefficient	0.1814	0.1694				
t-ratio	4.43	2.69				
coefficient	0.1659		0.1482			
t-ratio	3.78		2.35			
coefficient	0.1891			-0.5013		
t-ratio	4.16			-2.29		
coefficient	0.1813				0.0712	
t-ratio	3.04				1.49	
coefficient	0.1788					-0.0766
t-ratio	2.92					-1.63
R2		0.4879	0.4597	0.4272	0.3456	0.3208

Notes: Determinants for the year 1994, except (a) EU RCI and EQI indicators; shares of Pavitt sectors, from the earliest available values, 2010 and 1995, respectively; (b) civic sense, technological potential, and infrastructure endowment, available only for 1996, 1991, and 1987, respectively.

Source: Authors' elaboration

random effect panel vector autoregressive model (with cross-subsectional heterogeneity) to provide estimates of ESIF region-specific multipliers for eighteen Italian administrative regions throughout the 1944–2016 period. We exclude Valle D'Aosta and Molise from the estimation sample to avoid obtain multiplier values more amenable to an informative analysis of their determinants.

Our evidence highlights a fair degree of substitutability between ESIFs and other fiscal expenditure variables, especially nationally funded government investment. This behaviour somehow contradicts the principle of additionality under which EU resources should be additional and not a substitute for other national and/or regional funding sources. As for gross fixed capital formation, a crowding-in effect generally emerges for shocks to ESIFs.

We obtain results that are very heterogenous across regions, supporting the idea that spending decisions may have widely different effects within a given country. However, a shock to the RF, our measure of ESIFs, seems to have a positive impact on GDP in most regions, with multipliers that increase over the time horizon and are significant in the long run for various regions, especially in the Mezzogiorno.

When we produce an exploratory analysis of the differences of multipliers across regions, we find significant correlations between (five-year) ESIF multipliers and a some of their potential determinants. There exists a positive and significant association of the value of multipliers with labour slack and technological capability.

Finding that ESIF multipliers are tendentially larger in the Mezzogiorno has obvious relevance for the decade-long debate on the divide between the Mezzogiorno and the rest of the country. Our results are robust across different identification schemes for fiscal shocks and are qualitatively unchanged for two different measures of potential GDP. We believe that this evidence is sufficiently robust to imply that a phasing out of ESIFs could have a very detrimental impact for the reduction of territorial disparities in Italy.

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I moltiplicatori dei Fondi Strutturali e di Investimento Europei nelle regioni italiane

Sommario

Negli ultimi anni si è assistito a un ampliamento dei divari territoriali anche a causa delle profonde trasformazioni che stanno attraversando le economie europee (digitalizzazione, globalizzazione, pandemia e crisi politiche). In tale scenario diventa particolarmente importante quantificare l'impatto dei Fondi Strutturali e di Investimento Europei (SIE) sul PIL delle economie regionali. In questo lavoro si stimano i moltiplicatori dei Fondi SIE per le maggiori diciotto regioni amministrative italiane nel periodo

1994-2016. Gli elementi di novità relativamente a studi precedenti sono l'analisi in dettaglio del comportamento dinamico dei Fondi SIE, nonché dei fattori che guidano la determinazione dei loro moltiplicatori alla luce di un'analisi multivariata. Dalle stime emerge l'esistenza di sostituibilità dinamica tra i Fondi SIE e altre componenti della spesa pubblica, in contrasto con il principio di addizionalità proprio della politica di coesione. Inoltre, l'analisi interregionale dei moltiplicatori suggerisce che i loro valori siano positivamente associati alla dotazione tecnologica delle singole regioni e alla presenza in esse di risorse inutilizzate.

Cohesion Policy Impact on Regional Development Cross-sectional and Panel Data-based Spatial Analysis

Cristina Brasili, Pinuccia Pasqualina Calia*, Zbigniew Mogiła**

Abstract

Cohesion Policy have been the major tool for the EU to struggle against regional disparities. Its impact on regional development has always been an important research theme. The main aim of our paper is to analyse the impact of CP on the development of EU NUTS-2 regions in the period 2007-2018, by adopting a beta-convergence model approach, and trying to overcome its main limitations, i.e. endogeneity, spatial relationship and heterogeneity. In addition, we conduct analysis using both cross-sectional and panel data. Our findings show strong evidence of growth convergence between regions and a slightly positive impact of CP on less developed regions of the EU. Moreover, the models show that Cohesion Policy has a slightly negative impact on economic growth in the EU's richest regions.

1. Introduction

As the "geography of discontent" (McCann, 2020) and "revenge of places that do not matter" (Rodríguez-Pose, 2017; Rodríguez-Pose, Dijkstra, 2021) show, greater spatial disparities can lead to increasing dissatisfaction with the economic system and harm the foundations of economic growth, social cohesion and even democracy. In the turbulent times we face, this issue grows in importance and requires an appropriate solution. One of the most powerful tools for dealing with regional disparities is the EU Cohesion Policy. All EU regions benefit from Cohesion Policy's resources which are, however, mostly allocated to those with a per capita GDP below 75% of the EU average (Objective 1 regions, later renamed "convergence regions" and, in the more recent programming cycle, "lagging"). The ability of Cohesion Policy to bring disadvantaged areas towards the level of the economic well-being of the most advanced regions of the European Union is still the subject

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of debate among both scholars and politicians. Importantly, a significant number of empirical studies evaluating Cohesion Policy have not resulted in a consensus on its effectiveness in achieving this goal in a widespread and generalized way.

An analysis of the body of literature, including the metanalyses by Davies (2017), Dall'Erba and Fang (2017), and the European Parliament (2019), on the Cohesion Policy impact on regional economic development, reveals three main types of research methods applied: econometric models (cross-section and panel data); policy evaluation methods (e.g. a Regression Discontinuity Design and Generalized Propensity Score Matching – GPS) and macroeconomic modelling. Their outcomes are often supplemented by specific case studies. The vast majority of econometric research investigates the impact at the NUTS-2 level that is the territorial level of implementation of the Cohesion Policy. Apart from limited data availability at finer levels of territorial disaggregation, analysis based on NUTS-2 regions is motivated precisely by their role in programming and implementing regional policies in the EU. In addition, the magnitude of public financial support needs to be large enough to be able to impact the economy. In fact, the Cohesion Policy funding allocated across NUTS-2 regions often exceeds 1% of regional GDP per year reaching sometimes much higher levels of 4-5% of GDP in lagging regions. Nonetheless, the literature provides no conclusive results as to the macroeconomic effectiveness of EU support.

With this paper, we aim to revisit the outcomes of the Beta-convergence model-based approach to Cohesion Policy impact analysis across EU NUTS-2 regions. To this end, we substantially augment a set of regional characteristics conditioning the scale of the Cohesion Policy effect. Moreover, we apply the growth model method for the 2007-2013 and the 2014-2020 EU programming periods, which are the most recent data on Structural Funds expenditure available. Finally, we use both cross-sectional and panel data and methods. Panel data allow us to focus on the cumulative Cohesion Policy effects produced throughout the whole period under study and to exploit the temporal dimension of Cohesion Policy impact.

We address the main criticisms of the Beta convergence model-based studies of Cohesion Policy, i.e., endogeneity, spatial dependence and heterogeneity. As stipulated by Fidrmuc *et al.* (2019), an endogeneity bias in the relationship between Cohesion Policy financial support and economic growth may find its source in the institutional set-up of Cohesion Policy, i.e., the preference for lagging regions (a downward bias). In addition, a spurious correlation between EU financial support and GDP growth may occur as a result of the conditional Beta-convergence, namely the fact that poorer regions tend to develop at a faster growth rate than richer regions. Hence, an upward bias is likely to distort the association between Cohesion Policy and regional growth. Finally, the endogeneity issue may result from omitted variables, i.e., structural specifics of regional economies that may put upward (e.g., due to more productive economies more likely to absorb Cohesion Policy funding and turn it into greater economic effects) or downward pressure (e.g., due to agriculture-driven economic structure) on the Cohesion Policy impact on GDP growth. Following Dall'Erba and Le Gallo (2008), we deal with the endogeneity problem using instrumental variables generated with the 3-group method (Kennedy, 1992).

In addition, we address two other important issues associated with the Beta-convergence approach, that is spatial dependence and spatial heterogeneity. The former implies that the economic performance of the region might be affected by economic processes going on in its neighbouring regions. This, in turn, indicates that Cohesion Policy -induced effects in adjoining territorial units are likely to influence the effects produced by EU funding in a specific region. Spatial heterogeneity is associated with various geographical patterns in terms of economic behaviour. These may be interpreted as different convergence clubs characterized by similar initial conditions and common steady-states. Technically, spatial heterogeneity can be reflected by varying coefficients (structural instability) and/or by varying error variances across observations (groupwise heteroskedasticity) (Dall'Erba, Le Gallo, 2008). In order to deal with the spatial autocorrelation and spatial heterogeneity problems, we use a spatial autoregressive model with dummy variables for lagging NUTS-2 regions (with below 75% of the EU GDP per capita), phasing-out regions (with between 75%-90% of the EU GDP per capita), and richest regions (with above 90% of the EU GDP per capita). Additionally, groupwise heteroskedasticity is addressed.

The structure of the paper is as follows. In section 2, we give a brief overview of the previous studies of CP impact analysis. Then, our empirical strategy and data are described (section 3). We subsequently present and discuss the results from the regression cross-sectional and panel models (section 4). The paper concludes by highlighting the key findings (section 5).

2. Literature Review

An analysis of the body of literature on the impact of the Cohesion Policy on regional economic development shows that a rich set of studies have been produced in the last 20 years using different approaches, mainly econometric analysis (based on cross-section or panel data) and policy evaluation studies[1].

1. A different approach uses macroeconomic models to estimate the Cohesion Policy expenditure cumulative multipliers: the QUEST model (Varga, in't Veld, 2009); the HERMIN model (Bradley, Untiedt, 2010; Bradley *et al*., 2009) and the RHOMOLO model (Monfort, 2012; Sakkas, 2018; Di Comite *et al.*, 2018). These studies identify some structural factors as the key drivers determining the macroeconomic efficiency of EU funding; however, the cumulative multipliers are merely used there to ensure comparability of impact outcomes across countries or regions.

In the former stream of literature, most of the studies implicitly or explicitly make use of β-convergence models, formally derived by Barro and Sala-i Martin (1992) from the neoclassical growth theory. Depending on the type of data, specific models, and reference period the results on the impact of the EU regional policy were mixed.

Rodriguez-Pose and Fratesi (2004) found some positive effects only for EU transfers dedicated to some specific sectors (the agriculture and the education sectors) while no significant effect for others (infrastructure and business support). Ederveen *et al.* (2006) using country-level data covering five-year periods from 1960-1965 through 1990-1995, find that European support did not improve the countries' growth performance, but it enhanced growth in countries with a "proper" institutional framework related to institutional quality and economic openness. Esposti and Bussoleti (2008), estimate a dynamic panel data model for the period 1989-2000 and find that growth convergence is influenced by Objective 1 transfers which affect the regional initial investment rate and eventually its steady-state level. The impact of the Objective 1 policy on growth, however, is generally quite limited and may become negligible and even negative in some regional cases.

Subsequent studies introduced spatial dependence in the analysis, evidencing the role of spatial spillover in the regional growth process. Ramajo *et al.* (2008), using data covering the years 1981-1996, explicitly model both spatial dependence and spatial heterogeneity, and find that regions in the EU Cohesion-Fund countries (Ireland, Greece, Portugal and Spain) were converging separately from the rest of EU regions with a faster conditional convergence rate in relative income levels. Moreover, they find significant geographic spillovers in the EU regional growth process. Dall'Erba and Le Gallo (2008) considering the years 1989–1999 model spatial spillover effects and control the potential endogeneity problem in the estimation of their impact. The results indicate that significant convergence takes place, but that the funds have no impact on it. A further analysis (Le Gallo *et al.*, 2011) investigates the heterogeneity of the impact of structural funds and although a weak global impact of Structural Funds is detected, local impacts are very diverse, with a positive influence on the growth of British, Greek, and southern Italian regions. Mohl and Hangen (2010) use instrumental variables and control for spatial spillover effects in the context of a panel data analysis over the period 2000-2006. Considering the breakout of the EU transfers among Objective 1, Objective 2 and Objective 3 payments, they find that only Objective 1 payments had some effects while considering all transfers together there is no effect at all. Bouayad-Agha *et al.* (2013) consider both spatial and temporal dynamics in assessing the impact of European cohesion policy on a dataset of 143 EU regions from 1980 to 2005. Objective 1 transfers directly affect regional GDP per capita growth rates, whereas total Structural

Funds do not; considering the spatial dimension of the panel brings to light a still significant, but less important, impact of Structural Funds.

Recently, a few studies extended the time span of the analysis and confirm the importance of accounting for spatial effects. Fiaschi *et al.* (2018) evaluate the effectiveness of the Cohesion Policy in EU regions for the period 1991-2008 based on a spatial growth model. Focusing on funds targeting Objective 1 regions, they find strong spatial externalities and a positive and concave effect on the growth of GDP per worker until the ratio funds/GDP reach some threshold. Other types of funds have nonsignificant effects or significant and positive effects but with limited size. Antunes *et al.* (2020) consider, as well, a spatial growth convergence model applied to panel data across the years 1995-2009, confirming the existence of conditional convergence and spillover effects but do not detect positive significant impacts from structural funds. Scotti *et al.* (2022) investigate the effects of EU Cohesion funds according to the financed sectors since different sectors may have different roles in stimulating economic growth and investments may have immediate positive effects for certain sectors while significant impacts only in the long run for others. Using spatial panel data models, they investigate the sectoral impacts on European regions over the period 2007–2014 and find that impacts are higher and persistent only for investments in certain sectors (energy, R&D, and transportation) and emphasize the role of spatial spillovers in generating higher impacts on economic growth not only in the recipient regions but also in the neighbours.

Another stream of literature addresses the evaluation of the effects of European regional policy using quasi-experimental methods for causal inference. Such studies focus on the EU transfers labelled Objective 1 which target the EU regions with GDP per capita below 75% of the EU average, and apply the Regression Discontinuity Design (RDD) (Becker *et al.*, 2010; 2013; 2018; Pellegrini *et al.*, 2013, Ferrara *et al.*, 2017; Cerqua, Pellegrini, 2018; Giua, 2017; Percoco, 2017; Gagliardi, Percoco, 2017), the Generalized Propensity Score (GPS) matching (Becker *et al.*, 2012) and the Synthetic Control Method (SCM) (Barone *et al.,* 2016) to compare recipient and not recipient regions. The results show a higher degree of coherence since they all provide evidence of a positive and significant effect of transfers on GDP per-capita growth. Some studies have evidenced, however, that above a given level of transfers, no additional effects would be generated (Becker *et al.* 2012; Cerqua, Pellegrini, 2018) and that the benefits tend to disappear as the transfers are stopped (Barone *et al.*, 2016; Becker *et al.*, 2018). Moreover, the effectiveness of SCFs is found to be related to specific sectors, local economic structure, human capital endowment and quality of government institutions (Becker *et al.*, 2013; Ferrara *et al.*, 2017; Percoco, 2017; Gagliardi, Percoco, 2017).

3. Empirical Strategy and Data

Our starting point is a Beta-convergence model as shown by Equation 1. As EU NUTS-2 regions differ substantially in their socio-economic specifics, it is clear that their steady-states may be different as well. To this end, we use a conditional Beta-convergence model and augment it with the ratio of Cohesion Policy funding to GDP to be able to investigate its impact on the transitional growth rate:

$$g_t = \alpha + \beta y_0 + X\varphi + \mu CP + \varepsilon \qquad [1]$$

where for each region:

g_t is the average growth rate of per capita GDP between date 0 and t;

y_0 is the log per capita GDP level at date 0;

X is the vector of conditioning variables;

CP is the ratio of Cohesion Policy funding to GDP;

ε is an error term;

α, β, φ and μ are the unknown parameters to be estimated.

In order to address different specifics of the regions studied that tend to determine their steady states, we decide to use the following variables as conditioning factors:

- Population growth rate (POP_Growth) – a standard element of the neoclassical growth model computed by multiplying population growth rate, technological progress and depreciation rates.[2]
- Ratio of Gross Fixed Capital Formation to GDP (GFCF_GDP) – a proxy for saturation of the regional economy with physical capital.
- The share of individuals with higher education in the total population as a percentage of the country's average (Edu_High) - a proxy for human capital.
- The share of the agriculture sector in total GVA (Primary Sector) – a proxy for the structure of the regional economy.
- Population accessible within 1h30 by road as a share of the population in a neighbourhood of 120 km radius (Road_Acces) – a proxy for road accessibility of the region.
- Daily number of passenger flights as a percentage of the country's average (Air_Acces) – a proxy for air accessibility of the region.
- Population density (DENS) - a proxy for agglomeration effects.[3]

The selection of condition variables was largely determined by data availability. The covariates were checked for multicollinearity. The data sources are

2. Following Mankiw *et al.* (1992), we use 0.05 as the sum of technological progress and depreciation.
3. All variables are taken in logs.

shown in Table A.1 in the Appendix and Table A.2 provides basic descriptive statistics for the regional variables used in the econometric analysis.

As clearly stipulated by Dall'Erba and Le Gallo (2008), spatial heterogeneity might take the form of varying coefficients (structural instability) and/or varying error variances across observations (groupwise heteroskedasticity). In order to handle the former, we determined three spatial regimes (the group of regions)[4], i.e., the lagging regions with GDP per capita (PPS EU=100) lower than 75% (former Objective 1 regions); between, 75%-90% (phasing-out regions), and the most affluent ones with GDP per capita greater than 90% of the EU average. Moreover, we allow for varying error variances across observations, i.e., groupwise heteroskedasticity (Equation 2).

$$\begin{aligned} g_t = {} & \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \beta_1 D_1 y_0 + \beta_2 D_2 y_0 + \beta_3 D_3 y_0 + D_1 X \varphi_1 + \\ & + D_2 X \varphi_2 + D_3 X \varphi_3 + \mu_1 D_1 CP + \mu_2 D_2 CP + \mu_3 D_3 CP + \varepsilon \end{aligned} \qquad [2]$$

$$\varepsilon \sim N\begin{pmatrix} & \sigma_1^2 I_{n1} & 0 & 0 \\ 0, & 0 & \sigma_2^2 I_{n2} & 0 \\ & 0 & 0 & \sigma_3^2 I_{n3} \end{pmatrix}$$

where:

$D_1 - D_3$ are dummy variables qualifying the three regimes, i.e., lagging ($D1$), phasing-out ($D2$) and advanced ($D3$) regions, $\sigma_1^2 - \sigma_3^2$ the regime-specific constant error variances, $I_{n1} - I_{n3}$ are the identity matrices of dimensions equal to the number of observations in the three regimes in question.

We subsequently generated the spatial weighting matrix. To this end, we used the squared inverse great-circle distance between the centroids of regions i and j (d_{ij}^{-2}) in kilometers, defined as in Equation 3:

$$w_{ij} = \begin{cases} 0 \quad \text{if} \quad i = j \\ \dfrac{d_{ij}^{-2}}{\Sigma_1^j d_{ij}^{-2}} \quad \text{if} \quad d_{ij} \le D(k) \quad \text{for} \quad k = \{1;2;3;\} \\ 0 \quad \text{if} \quad d_{ij} > D(k) \end{cases} \qquad [3]$$

where w_{ij} is an element of the spatial weight matrix W in row i and column j.

It enables one to reflect the gravity-like relationship among regions which declines exponentially with distance (Dall'Erba, Le Gallo, 2008).

We use quartiles (k) of the overall distribution of great circle distances among all region pairs as a threshold distance, i.e., the lower quartile $D(1)$, the median

4. As an alternative, we used the G-I statistics developed by Ord and Getis, where two kinds of regions were detected, i.e. core and peripheral regions. Having run the regression models, it turned out that the second variant of the spatial regimes, i.e., that with lagging regions, phasing-out regions, and economically advanced regions, is characterized by better goodness of fit. Hence, we decided to go further only with this variant.

D(2), and the upper quartile D(3) of the great circle distance distribution. Each matrix is row standardized. Thus, the relative distance is taken into account.

As a result, the spatial lag-dependent variable was introduced to both models 1 and 2 giving the following model specifications:[5]

$$g_t = \rho W g_t + \alpha + \beta y_0 + X\varphi + \mu CP + \varepsilon \qquad [4]$$

$$\begin{aligned} g_t = {} & \rho_1 W g_{t1} + \rho_2 W g_{t2} + \rho_3 W g_{t3} + \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \beta_1 D_1 y_0 + \beta_2 D_2 y_0 + \beta_3 D_3 y_0 + \\ & + D_1 X \varphi_1 + D_2 X \varphi_2 + D_3 X \varphi_3 + \mu_1 D_1 CP + \mu_2 D_2 CP + \mu_3 D_3 CP + \varepsilon \end{aligned} \qquad [5]$$

where ρ indicates the level of spatial autocorrelation between regions.

Following Dall'Erba and Le Gallo (2008), we constructed instrumental variables using the 3-group method, advocated by Kennedy (1992) in the context of measurement errors and used in a spatial context by Fingleton (2003). For Cohesion Policy transfers, an instrumental variable was constructed that takes values 1,0 and -1 according to whether the transfer to GDP ratio is in the top, the middle or bottom third of their ranking, ranging from 1 to 248[6]. The outcomes of the tests for instrumental variables are shown in Table A.3 in the Appendix.

In order to include the temporal dimension of the relationship between Cohesion Policy support and economic growth, we moved on to panel data specifications. The Hausman test clearly showed the fixed effects estimator as the most appropriate for further analysis.[7]

Consequently, the following model specification was constructed:

$$\begin{aligned} g_t = {} & \rho_1 W g_{t\,1} + \rho_2 W g_{t\,2} + \rho_3 W g_{t\,3} + \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \\ & + \beta_1 D_1 y_{t-1} + \beta_2 D_2 y_{t-1} + \beta_3 D_3 y_{t-1} + D_1 X \varphi_{1t} + D_2 X_t \varphi_{2t} + D_3 X \varphi_{3t} + \\ & + \mu_1 D_1 CP_t + \mu_2 D_2 CP_t + \mu_3 D_3 CP_t + \mu_r + \tau_t + \varepsilon_t \end{aligned} \qquad [6]$$

where μ_r are fixed effects in region *r*, and τ_t are the time effects.

Simulations were carried out for time lags ranging from 0 to 4 years. This enables us to investigate how the relationship between Cohesion Policy transfer and GDP growth changes over time when supply-side effects of EU funding kick in.

5. Like Dall'Erba and Le Gallo, (2008), we use an autoregressive spatial model. As the ultimate goal of the EU Cohesion Policy is to bridge the gap between advanced and lagging regions, this type of spatial model allows us to account for the role of the development level of neighbouring regions in stimulating regional growth. As proximity to more advanced regions is likely to stimulate economic growth, it should be taken into account when investigating the CP impact.

6. Other instrumental variables were also constructed. Specifically, we tested the role of the spatially lagged instrumental variable based on the 3-group method. The tests performed, however, did not support them as an appropriate instrument.

7. x^2=911.89, p-value = 0.0000.

4. Results

4.1. Cross-section Models

Table 1 presents the cross-section regression results for the model specifications, i.e. without spatial regimes (Models 1 and Model 2) and with spatial regimes (Model 3).

Model 1 and Model 2 confirm that there is a Beta-convergence in the EU (about 1% rate). However, when the spatial regimes kick in (Model 3), the results do not provide strong evidence for significant differences between the well-performing and the lagging regions, while phasing-out regions seem to not converge. With respect to conditioning factors, the important role of physical capital, i.e., gross fixed capital formation, in determining regional growth is clearly shown. There is also some evidence that regions with agriculture-driven economic structures grow at a smaller rate. In addition, the regression outcomes in the model specifications without spatial regimes do not point to spatial dependency as an important factor affecting regional development but when spatial regimes kick in we find that there is a significant spatial dependence found in the case of lagging regions; put differently, the economic dynamics in the neighbouring regions have a positive impact on the economic performance of a specific regional economy when considering lagging regions. Moreover, the negative relationship between population density and economic growth seems to support the Beta-convergence, that is a relatively sluggish GDP growth rate in more advanced regions exhibiting often great agglomeration advantage.

Regarding the impact of the Cohesion Policy, Model 1 and Model 2 (Table 1) show that Cohesion Policy has a slightly negative impact on economic growth in the EU regions. When one looks, however, at different types of regions as shown with Model 3 (Table 1), there is evidence of a positive significant effect of EU funding on the GDP growth rate for lagging and phasing-out regions and this negative effect might be due only to the richest EU regions. Even though some negative Cohesion Policy effects are shown in Dall'Erba and Le Gallo (2008) or Scotti *et al.* (2022), it seems that cross-section results are still affected by the endogeneity problem. We make an attempt to overcome this problem estimating panel data models.

4.2. Panel Data Regression Models

Even though, the pooled OLS model specification shown by Model 6 (Table 2) confirms the results of the cross-section models presented in Section 4.1., Models 4 and Model 5 (Table 2) clearly show the positive and statistically significant impact of EU support on economic growth. The Cohesion Policy impact (0.02%)

Table 1 – Regression Results (Cross section data)

Dependent Variable GDPPC_Growth	*Model 1 OLS*	*Model 2 2SLS-LAG*	*Model 3 2SLS-LAG with spatial regimes*
Variables in logs	*GDPPC_Growth*	*GDPPC_Growth*	*GDPPC_Growth*
GDPPC_2008	-0.00789*** (0.00252)	-0.00760** (0.00344)	-0.0155*** (0.00501)
GDPPC_2008 (Objective 1)			-0.0109 (0.00691)
GDPPC_2008 (Phasing-Out)			0.0739*** (0.0269)
GDPPC_Growth_Spatial_Lag		0.0859 (0.184)	0.642 (0.435)
GDPPC_Growth_Spatial_Lag (Objective1)			3.567** (1.577)
GDPPC_Growth_Spatial_Lag (Phasing-Out)			-0.363 (0.679)
GFCF_GDP	0.00613** (0.00281)	0.00601 (0.00412)	0.0265*** (0.00507)
GFCF_GDP (Objective1)			-0.00918 (0.0113)
GFCF_GDP (Phasing-Out)			0.0173 (0.0133)
Primary Sector	-0.00118* (0.000673)	-0.00112* (0.000646)	-0.00351*** (0.000893)
Primary Sector (Objective1)			-0.00275 (0.00302)
Primary Sector (Phasing-Out)			0.00448 (0.00505)
Edu_High	0.00227 (0.00253)	0.00213 (0.00279)	-0.000648 (0.00210)
Edu_High (Objective1)			0.00347 (0.00771)
Edu_High (Phasing-Out)			-0.0149* (0.00849)
Population Growth	-0.0334 (0.0380)	-0.0320 (0.0775)	-0.262*** (0.0530)
Population Growth (Objective1)			0.109 (0.326)
Population Growth Phasing-Out)			0.0481 (0.183)
Population Density	-0.00160** (0.000690)	-0.00157** (0.000642)	-0.00184* (0.00111)
Population Density (Objective1)			0.00514 (0.00484)

(...continue...)

(...continue...)

Dependent Variable GDPPC_Growth	*Model 1 OLS*	*Model 2 2SLS-LAG*	*Model 3 2SLS-LAG with spatial regimes*
Variables in logs	*GDPPC_Growth*	*GDPPC_Growth*	*GDPPC_Growth*
Population Density (Phasing-Out)			0.00873 (0.00575)
Road_Access	0.00106 (0.000685)	0.00110** (0.000550)	0.00319** (0.00135)
Road_Access (Objective1)			-0.000623 (0.00334)
Road_Access (Phasing-Out)			0.000699 (0.00387)
Air_Access	-0.000145 (0.000361)	-0.000149 (0.000354)	-0.000987 (0.000862)
Air_Access (Objective1)			-0.000491 (0.00123)
Air_Access (Phasing-Out)			0.00660*** (0.00239)
Objective 1			0.144 (0.235)
Phasing-Out			-0.646** (0.275)
Cohesion Policy _GDP	-0.00128** (0.000611)	-0.00123 (0.000776)	-0.00490*** (0.00156)
Cohesion Policy _GDP (Objective 1)			0.00714* (0.00394)
Cohesion Policy _GDP (Phasing-Out)			0.0124*** (0.00413)
Country-specific effects	YES	YES	YES
Constant	0.0765** (0.0351)	0.0749 (0.0603)	-0.000697 (0.0697)
Observations	248	248	248
Adjusted R-squared	0,9016	0.9148[a]	0.681[a]

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; a: Pseudo R^2.
Source: Authors' elaboration

is slightly lower than that reported by Di Caro and Fratesi (2022), i.e., 0.07% for the EU-15 and 0.05% for the new member states. Importantly, we found only direct effects statistically significant (Table A.4 in the Appendix) but no evidence was provided for the spatial spill-over effects of EU funding. Again, there is strong evidence of growth convergence between regions. As reported also in the most recent literature (Bouayad-Agha *et al.*, 2013; Fiaschi *et al.*, 2018; Antunes *et al.*, 2020, Scotti *et al.*, 2022), the spatial dependence between neighbour regions

Table 2 – Panel Data-based Analysis

Variables in Logs	*Model 4* *2SLS* *GDPPC_Growth*	*Model 5* *FE* *GDPPC_Growth*	*Model 6* *Pooled OLS* *GDPPC_Growth*
Cohesion Policy_GDP	0.0238***	0.0146***	-0.0168***
	(0.00645)	(0.00341)	(0.00329)
GDPPC_base	-0.707***	-0.693***	-0.0902***
	(0.0405)	(0.0387)	(0.0106)
Population Growth	0.0946	0.100	-0.412***
	(0.0704)	(0.0703)	(0.0793)
Population Density	-0.499**	-0.530***	-0.000683
	(0.197)	(0.201)	(0.00521)
Edu_High	-0.0215	-0.0154	0.00131
	(0.0226)	(0.0223)	(0.0110)
Gdppc_Growth_Spatial_Lag	0.489***	0.475**	0.773***
	(0.169)	(0.185)	(0.231)
GFCF_GDP	0.0201	0.0196	0.158***
	(0.0227)	(0.0233)	(0.0200)
Primary Sector	-0.0673***	-0.0682***	-0.0260***
	(0.0221)	(0.0228)	(0.00547)
Time Effects	YES	YES	YES
Constant		8.597***	0.348**
		(1.151)	(0.134)
Observations	1,759	1,759	1,759
R-squared	0.687	0.692	0.504
Number of _ID	220	220	220

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration

strongly influences GDP growth. Overall, allowing for fixed effects seems to cope better with the endogeneity issue than cross-section specifications.

As Cohesion Policy is intended to produce long-term effects that would be seen after EU support terminates, it is increasingly important to look at how Cohesion Policy impacts change over time. To that end, we estimate our models with different time lags (Table 3). The impact of the Cohesion Policy seems to grow over time as the long-run supply-side effects appear. These result from, among other things, improved transportation infrastructure, greater human resources, and innovation. The role of EU support in the implementational phase is not shown in the results. The short-term demand-side effects might be compensated

Table 3 – CP Impacts on GDP Growth – Different Time Lags

	t	*t-1*	*t-2*	*t-3*	*t-4*
	2SLS				
Cohesion Policy_GDP	0,0046	0,0015	0.0074*	0.0201***	0.0238***
	FE				
Cohesion Policy_GDP	0,0006	0.0039***	0.011***	0.0128***	0.0146***
	POOLED OLS				
Cohesion Policy_GDP	-0.0053***	-0.0042***	-0.0067***	-0.0118***	-0.0168***

Source: Authors' elaboration

by, e.g., crowding-out effects, fiscal burden, and domestic co-financing which lowers additionality of EU support. The positive effects of EU funding become only significant two years after its implementation.

In addition[8], as shown in Table 4, the richer regions seem to be more effective in converting the EU support into economic effects in the short run. However, as their economies are relatively better abundant with physical capital stock and human capital, the supply-side effects in the longer term are not statistically significant. Conversely, the lagging regions tend to have the greatest effects from payments as the phase-in period ends and the supply-side effects begin to contribute to GDP growth.

5. Conclusions

Structural Funds are an important part of the European integration project and the capacity of Cohesion Policy to promote regional economic growth has been controversial for decades. Up to now, scholars have not been unanimous about the role of Structural Funds on growth (Dall'Erba, Fang, 2017). However, this kind of analysis is very relevant if we think that an increasing part of the Community budget has been devoted to Cohesion Policy, about forty per cent in the nowadays programming period.

In this paper, we go further with the results produced by the Beta-convergence modelling framework for economic growth. We pay attention to both the presence of spillover effects among regions and the potential risk of endogeneity of the Structural Funds when estimating their impact. We contribute to the literature by using the method of Dall'Erba and Le Gallo (2008), however, with a much greater selection of indicators determining the regional steady state. In addition, as

8. The results of the panel data models with spatial regimes are not shown for the sake of brevity. The tables with detailed estimation outputs are available upon request.

Table 4 – CP Impacts on GDP Growth – Different Time Lags and Different Types of Regions

	t	*t-1*	*t-2*	*t-3*	*t-4*
	2SLS				
Developed	0,0041	0,0017	0.0126***	0.0194***	0,0058
Lagging	-0.0068*	-0,0049	-0.0148***	0,0000	0.0371**
Phasing out	-0,0013	0,0019	-0,0066	-0,0254	0,0373
	FE				
Developed	0,0004	0.0040**	0.0102***	0.0107***	0.0067*
Lagging	0,0003	-0,0027	-0.0057**	0,0047	0.0161**
Phasing out	0,0033	0,0027	0,0003	-0,0074	0,0118
	POOLED OLS				
Developed	-0.0057***	-0.0046***	-0.0067***	-0.0139***	-0.0181***
Lagging	-0,0012	-0,0005	0,0027	0.0226***	0.0355***
Phasing out	0,0050	0.0058**	0,0063	0,0034	0,0054

Source: Authors' elaboration

Dall'Erba and Le Gallo (2008) cover the period 1989-1999, another contribution is to use their method for modelling regional EU economic growth also on the basis of the more available recent Cohesion Policy expenditures, that is 2008-2018.

Our findings (both cross-section and panel models) confirm strong evidence of growth convergence between regions and a significant influence of the population density and the share of the agriculture sector in the economy as conditioning factors. Moreover, as reported also in the most recent literature, the spatial dependence between neighbour regions strongly influenced the growth. While, considering the different groups of regions, the impact of Cohesion Policy expenditure on growth remains less conclusive and unequivocal.

In fact, our analysis highlights a differentiated impact of the Cohesion Policy on regional economic growth for different types of regions. Specifically, the regression results (cross-section model) show a slightly positive impact of Cohesion Policy on less developed regions of the EU and for phasing-out regions while negative impacts were found for well-performing regions. Even though some negative Cohesion Policy effects are also shown in Dall'Erba and Le Gallo (2008) or Scotti *et al.* (2022), it seems that our results are still affected by the endogeneity problem. The richer regions receive less support as compared to GDP than lagging regions and it could be that the Cohesion Policy effects in more advanced regions over the period considered could be outweighed by the costs of EU intervention, e.g., the crowding out effect, a greater fiscal burden borne by net contributors to the EU budget. Moreover, in the panel data model-based outcomes the Cohesion Policy impact (0.02%), is positive and statistically significant even if is slightly lower than that reported by Di Caro and Fratesi (2022), in the period 1989-2015, i.e. 0.07% for the EU-15 and 0.05% for the new member states.

Moreover, our results show strong evidence that the Cohesion Policy impact grows over time as the long-run supply-side effects kick in, while the role of EU support in the implementational phase does not come out. In fact, the effect of Structural Funds becomes significant only two or more years after the payments probably the short-term demand-side effects might be compensated by, e.g., crowding-out effects, fiscal burden, and domestic co-financing which lowers the additionality of EU support. The richer regions seem to be more effective in converting the EU support into economic effects in the short run. As their economies are relatively better abundant with physical capital stock and human capital, the supply-side effects become lower and a little less significant in the longer term. On the contrary, the lagging regions tend to have the greatest effects from Structural Fund payments after some years since the beginning of the programming period when the supply-side effects begin to contribute to economic growth.

Our findings call for a better adjustment of the Cohesion Policy to the economic and the social structure of different groups of EU regions for the future.

One step forward to this kind of implementation has already been done, in nowadays programming cycles, by conditioning the amount of EU Structural Fund devoted to each region not only on the level of GDP per capita. In fact, while the main criterion for determining funding has been remained relative prosperity, regions can also benefit from additional premiums based on socio-economic and environmental factors: unemployment (particularly youth unemployment), level of education, greenhouse effect and migration. In line with this EU strategy, the place-based approach should not become an artefact of the past, but it has to be competently and purposefully implemented specifically by each region in the programming phase of Policy Cohesion. The implementation of Cohesion Policy with these characteristics calls for high institutional quality and considering its role in the analysis could be the direction of possible future research development.

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Impatto della Politica di Coesione sullo sviluppo delle regioni – Analisi panel spaziale e cross-section

Sommario

La Politica di Coesione è stata (ed è) il principale strumento di contrasto e riduzione delle disparità regionali dell'Unione europea e quindi, l'analisi del suo impatto sullo sviluppo regionale continua ad essere un rilevante tema di ricerca. Il principale obiettivo del nostro contributo è di analizzare, appunto, l'impatto della Politica di Coesione sullo sviluppo delle regioni dell'UE (a livello NUTS-2) nel periodo 2007-2018. A tal fine, utilizziamo l'approccio della beta-convergenza cercando di superarne i principali limiti, affrontando adeguatamente il problema dell'endogeneità dei trasferimenti, l'esistenza di dipendenza spaziale e l'eterogeneità. L'analisi sarà condotta, inoltre, utilizzando dati cross-section e panel. I nostri risultati evidenziano, nel periodo considerato, una rilevante convergenza tra le regioni e un più limitato ma positivo impatto della Politica di Coesione sulle regioni in ritardo di sviluppo. Inoltre, i risultati sembrano mostrare un impatto lievemente negativo della Politica di Coesione sulla crescita delle regioni più ricche dell'UE.

Appendix

Table A.1 – Data Sources

Variable	*Description*	*Source*
CP_GDP	The ratio of EU payments (ERDF, CF and ESF regionalized and modelled) to GDP	European Commission
GDPPC_base	Initial GDP per capita level in mln EUR	Eurostat/ARDECO
GDPPC_Growth	GDP per capita growth rate	Own calculations
GDPPC_Growth_Spatial_Lag	Spatial lag of GDPPC_GROWTH	Own calculations
Population_Growth	Population growth rate plus the sum of technological progress and depreciation (0.05)	Own calculations
Population_Density	Population density	Eurostat
GFCF_GDP	The ratio of Gross Fixed Capital Formation to GDP	Eurostat/ARDECO
Primary_Sector	The share of agriculture in total GVA	Eurostat/ARDECO
Edu_High	The share of individuals with higher education in total population	Eurostat
Road_Access	Population accessible within 1h30 by road, as share of the population in a neighbourhood of 120 km radius	DG Regio, reference year: 2016
Air_Acces	Daily no. of passenger flights	Eurostat/EuroGeographics/ National Statitical Institutes, reference year: 2016

Source: Authors' elaboration

Table A.2 – Descriptive Statistics of Control Variables

	CP/GDP	*GDP pc. growth*	*GFCF/GDP*	*Higher aducation*	*Share of primary sector in total GVA*	*Population growth*	*Population density*	*Air accessibility*	*Road accessibility*
N	248	248	248	248	248	248	248	248	248
Mean	0.07	0.02	0.21	27.63	0.03	0.50	367.56	482.30	87.54
Median	0.01	0.02	0.21	27.30	0.02	0.50	132.63	225.97	66.41
Min	0.00	-0.04	0.12	11.40	0.00	0.47	3.35	0.12	1.14
Max	0.57	0.05	0.42	49.30	0.12	0.54	7172.27	2939.79	281.40
CV	1.54	0.99	0.18	0.32	0.90	0.02	2.23	1.20	0.80

Source: Authors' elaboration

Table A.3 – Endogeneity Tests (Cross-section models)

	Model 2 *2SLS*	*Model 3* *2SLS* *with spatial regimes*
Underidentification test (Kleibergen-Paap rk LM statistic)	142.6	0.000
Chi-sq(1) p-value	0.000	1.000
Weak identification test (Cragg-Donald Wald F statistic)	288.3	40.7
Hansen J statistic	Identified	Identified
Endogeneity test	0.049	10.2
Chi-sq(3) p-value	0.825	0.0173

Source: Authors' elaboration

Table A.4 – Direct, Indirect and Total Effect of CP Transfers on GDP Growth (Panel data models)

	Coefficient	*Std. Error*	*z*	*P>z*
Direct effect				
CP_GDP	0,012412	0,00357	3,48	0,001
Indirect effect				
CP_GDP	0,008301	0,01431	0,58	0,562
Total effect				
CP_GDP	0,020712	0,017419	1,19	0,234

Source: Authors' elaboration

The Impact of Spatial Spillovers on Cohesion Funds' Effectiveness: A Spatial Panel Analysis for the Italian Provinces

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Abstract

The aim of this work is to evaluate the impact of spatial spillovers on the effectiveness of projects financed in the Italian provinces (NUTS-3) by the European and national cohesion policy during the 2007-13 and 2014-20 programming periods. The fall-out of the economic effects of a public intervention outside the directly treated areas is certainly desirable. However, this may generate a displacement effect when the policy affects mainly more neighbouring territories. We employ a panel econometric strategy that incorporates spatial autocorrelation patterns between neighbouring provinces by estimating a spatial panel model. We disentangle the total policy impact into direct effects on the per capita GDP growth of the treated provinces and indirect (spillover) effects captured by neighbouring areas. The paper also examines the change of policy effectiveness and spillover direction across the Great Recession by testing whether regional policy has acted as a resilience factor in local economies. The data set was reconstructed from Opencoesione database and deals, for the first time in the literature, with registered expenditures related with completed projects. Our main results show that, in Italian provinces, during the considered period, spatial spillovers have a positive impact on European and national cohesion policies' effectiveness, in addition to direct effects. In the crisis years, spatial spillovers have drastically reduced and this may have caused a reduction in cohesion policy effectiveness.

1. Introduction

Cohesion funds are addressed to reduce economic imbalances among regions in the European Union. This specific European economic policy deals with the allocation of resources to regions in structural deficit with defined convergence objectives.

The policy has acquired specificity over time since the unequal well-being distribution has required targeted public intervention. The relevance of GDP heterogeneity at the European level also lies in the implications it may have in the

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society. Indeed, income imbalances is one of the possible causes of social tensions and popular discontent (Bénabou, 1996). In addition, the process of European unification itself needs to receive strong popular support. Therefore, regional policy may be seen as a channel to increase consensus towards the EU since it has been empirically demonstrated that the decrease in votes towards Eurosceptic parties is associated also by greater investment in cohesion (Rodriguez-Pose, Dijkstra, 2020).

The implementation of cohesion policy has evolved over time. Starting from 1988 the allocated amount has been calibrated more on regional economic performance. Previously, the Funds' shares were assigned at a national level regardless of regional context indicators.

After the establishment of the European Regional Development Fund (ERDF), starting from the 1989-1993 programming period and through the following ones, a specific feature of European regional policy has become the distinction of resources by thematic area.

To mention the most recent programming periods, in the 2007-2013, allocations amounted to 347 billion, in the 2014-2020 period they increased to 352 billion, the equivalent of more than a third of the EU budget.

The Partnership Agreement drawn up by each member State, in collaboration with the European Commission, binds the national and regional Operational Programs (OP) to assume specific measurable targets, in relation also to the financial allocations. Therefore, the analysis of the effectiveness of cohesion funds in reaching predetermined targets has become more and more relevant at the regional level.

Four principles (concentration, multiannual programming, partnership, and additionality) are applied and the regions are divided in a binary way according to their level of per capita GDP, if this is less than 75% of the European average per capita GDP, the regions are part of the main Objective[1].

As all public investment interventions, cohesion projects may potentially generate relevant spatial spillover effects, especially when place-based policy features are explicitly considered.

In terms of policy making, there are relevant issues to investigate such as: the direction of spatial spillovers, the specific effectiveness of the policy in the treated regions, the dimension of crowding-out effects when the prevailing impact occurs in the neighbouring territories.

This paper contributes to shed light on these issues by measuring spatial spillovers related to cohesion investment projects by distinguishing direct from indirect effects. To carry out the analysis, we use, for the first time in literature, a project-based data of fully operational projects on Italian provinces during the latest programming periods (2007-2013 and 2014-2020) by considering also the

1. "Growth and employment" in 2014-2020, which replaced the "Convergence" Objective of the 2007-2013 programming period and "Objective 1" of the previous ones.

effect of the Great Recession which may have played a role on changing the direction of the spillover effects and on modifying the regional policy impact.

Our objective is also to determine whether the phenomenon of spatial spillover is more relevant for cohesion policy with respect to other public investment policies. In Italy, for instance, the national government also invests its own resources on specific cohesion targets, so our evaluation is also extended to National cohesion impacts.

The rest of the work is structured as follows: the second section is devoted to the theoretical background on the occurrence of spatial spillovers on place-based policy, the third one reviews the prevailing literature while the research design and the main results, are included in section 4 and 5, respectively. A final (sixth) section concludes with policy implications.

2. Cohesion Policy and Spatial Spillovers

To make the cohesion intervention effective, the financed projects should be tailored around the needs of each territory. In both public debate and empirical literature, there is no unanimous agreement on the impact of European regional policy in achieving its objectives of economic growth and convergence.

As for the role of spatial proximity on policy effectiveness, Barro (1990) believes that public intervention may act as a sort of "productive expenditure", especially when dealing with transport infrastructures, communication networks and business support infrastructures which are among the typical modes of intervention of cohesion policy.

On a different ground, the analysis of agglomeration and dispersion forces of economic activities by the New Economic Geography scholars (i.e., Baldwin *et al.*, 2003), disputes the hypothesis that public intervention is always effective in reversing the regional growth paths. Indeed, in a North-South equilibrium, a condition of path-dependence can occur and this could make public intervention unsuitable for fostering the economic convergence. Among other things, investments in cohesion specifically aimed at adapting transport infrastructures in lagging regions may lead to a reduction in transport costs and, by this way, may determine a concentration of productive activities that, ultimately, could favour income divergence instead of convergence.

Therefore, the occurrence of undesired effects in policy implementation must be considered as a potential pitfall and the spatial element must be taken into account. In particular, a possible effect is that, due to spatial proximities and interactions[2], the policy outcomes may occur in the neighbouring territories and not in the treated ones.

2. To quote Tobler (1970), the father of the so-called "First Law of Geography", "everything is related to everything else, but near things are more related than distant things". This sentence

Hence, in evaluating the impact of a public policy, aimed at generating territorial development, it is important to measure spillover effects caused by spatial interaction and in particular by spatial proximity. When the gains of public investment projects are *also* captured by the territories adjacent to treated areas, spillover effects are inherently positive and desirable. Conversely, may happen that the effects of regional policy are caught *only* by neighbouring territories, thus generating displacement effects.

This paper evaluates the effectiveness of cohesion policy by looking at the completed projects in the last two programming periods before the current one (2007-2013 and 2014-2020) and referring to the Italian case. To measure spatial spillover effects we employ specific econometric techniques that incorporate the spatial autocorrelation pattern between neighbouring territories. The period under evaluation covers the Great Recession years. Therefore, we also control for the effects of the crisis by looking at the potential change of spillovers during severe downturns.

3. Related Literature

The economic literature dealing with the impacts of regional cohesion policy is vast and there is no unanimous agreement on its effectiveness in achieving the target objectives. The lack of consistency between the results may be due to a multiplicity of factors. The choice of the specific focus to analyse and the methodology used play the most important roles.

Prevailing methods in the empirical literature range from OLS to GMM, from panel data methods to Regression Discontinuity Design (see, for instance, Becker *et al*., 2010; Pellegrini *et al*., 2013; Gagliardi, Percoco, 2017; Giua, 2017; Crescenzi, Giua, 2020). Macroeconomic models are also used (Bradley *et al*., 2003; Varga, Veld, 2011).

A specific focus is the potential trade-off between effectiveness and efficiency. Even if the policy reaches its goal of reducing disparities in regional growth processes (effectiveness), the principle of efficient allocation of the resources would be lost when most of the financial funds were distributed to regions that are already leading in economic performance (Pieńkowski, Berkowitz, 2016).

The trade-off between equity and efficiency is traced in the works of Fratesi and Perucca (2014, 2019) which conclude that the effectiveness of the Structural Funds is mediated by the favourable territorial context. Cappelen *et al*. (2003) have already pointed out that cohesion policy was more effective in the most advanced European countries between 1980-1997. Similarly, Ederveen *et*

expresses the concept, widely developed in literature, according to which the first source of interaction is due to spatial proximity.

al. (2006), concluded that the efficacy of the Structural Funds is conditioned by favourable structural context elements including institutional quality. Such conclusion has been stressed also by Rodrìguez-Pose and Garcilazo (2015). Conversely, Mohl and Hagen (2010) and Pinho *et al*. (2015) have not found a relevant role for local economic conditions.

Few studies have yet considered the effect of the Great Recession, such as Merler (2016), Bachtrögler (2016) and Becker *et al*. (2018). Among these, the first study found a positive effect of cohesion policy even in the crisis period. No spatial spillovers were included in these analyses.

As for studies focusing on the Italian case, Percoco (2005) found that only two southern Italian regions (Apulia and Basilicata) experienced a very good performance from cohesion Funds. Aiello and Pupo (2012) underlined a greater impact on the Southern regions compared to the Northern ones; Giua (2017) traced a positive impact concentrated in specific strategic sectors and Coppola *et al*. (2020) concluded that European cohesion funds explained economic growth more than national cohesion funds.

Also the analyses capturing the impact of spatial effects did not reach unanimous results. Dall'Erba and Le Gallo J. (2008) first implemented a spatial lag model for the European NUTS-2 level regions in the period 1989-1999. They found that the Structural Funds did not contribute to the convergence process and that the spatial effects were quite relevant. Breidenbach *et al*. (2019) analysed the influence of the funds on per capita GDP growth of 127 European regions in the period 1997-2007 in the context of a spatial Durbin model (SDM) and show a negative effect on growth due to spatial spillovers. Hruza et. al (2019) estimated a SAR model for Czech Republic regions in the period 2004-2015, by obtaining a positive effect of cohesion policy and positive strong spillover effects across areas. Antunes *et al*. (2020) used a spatial Durbin model to evaluate the growth of 95 European regions in the period 1995-2009 and found neither a direct nor an indirect policy effect. Falk and Sinabell (2008) implemented a cross-sectional spatial lag and spatial error model for 1.084 NUTS-3 European regions over the period 1995-2004 stressing the relevance of spatial effects. Crescenzi and Giua (2020) employed the spatial extension of the regression discontinuity design method for European NUTS-3 areas in the period 2000-2014, tracing a more than pronounced impact in Germany and the United Kingdom. Fiaschi *et al*. (2018) assessed the influence of European funds in increasing the average annual growth rate of labour productivity in 175 European regions during 1991-2008. From SDM estimation it appeared that the funds addressed to the Objective 1 regions were important for the growth of the same areas (direct effect), but also have a significant indirect spillover effect.

In synthesis, from the international literature it emerges that spatial spillover effects are not negligible with some discrepancy across the studies. In addition, very rarely studies concentrating on the Italian case have considered spatial effects explicitly.

Empirical studies in the literature always use commitments or payments data to measure the Structural Funds' impact. While these data are useful to trace the progress of a public program, they may generate biases in the assessment of the impacts since they include information related to blocked or incomplete projects.

Our spatial analysis in the following section deals with some pitfalls that we found in the previous literature. First, it takes into account of the previous considerations by using actual project data and eliminating uncompleted projects. Second, it analyses the differential effects of a severe global crises (the Great Recession) on the impact of Structural and Investment Funds. Thirdly, it contrasts this effectiveness with the one of an alternative investment policy (the national cohesion policy) by investigating the relative role of spatial spillovers in the two contexts.

4. Empirical Framework

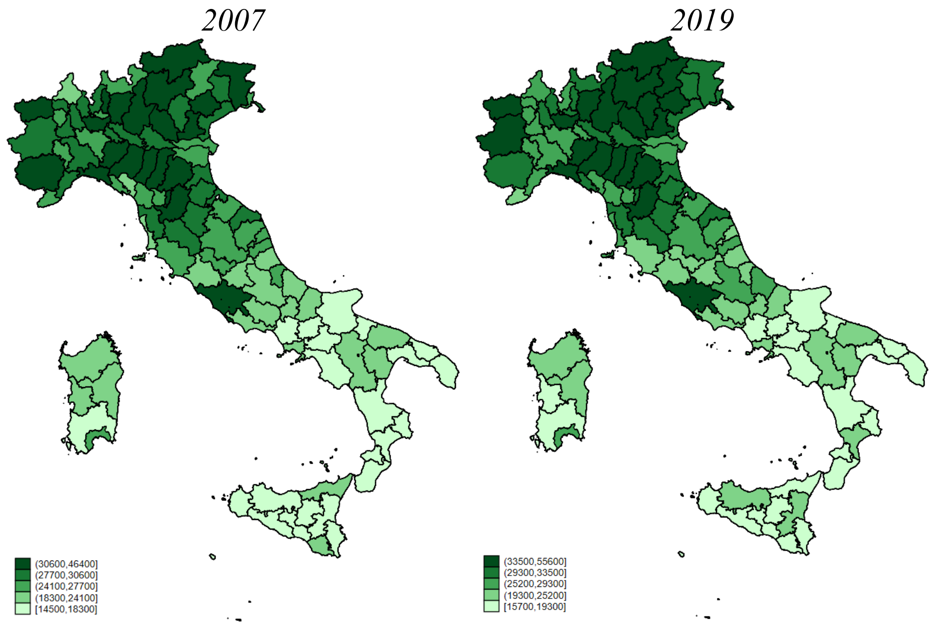
Our analysis focuses on Italian provinces during the period between 2007 and 2020. As shown in Figure 1, regional gaps at NUTS-3 level are substantially unchanged in the period under consideration.

4.1. Data

Our panel data set was reconstructed starting from the data on *Opencoesione*, the Italian cohesion policies database managed by "*Dipartimento per le politiche di coesione*", in collaboration with "*Agenzia per la coesione territoriale*" and "*Ragioneria generale dello Stato*". The main purpose of this database is to increase the transparency of expenditure flows by including detailed information relating to each project. It is also useful for potential beneficiaries of the European support since it describes all funding opportunities.

We have chosen this data source because we believe that a project-based disbursement data can be more representative than accounting data (such as payments or commitments) to capture the impact of cohesion resources. As mentioned above, data commonly used in the empirical literature may introduce bias when the paid amounts refer to projects in progress or blocked which are not fully able of generating economic effects. The estimation of a model based on accounting variables may therefore bring to misleading result in the estimation of policy effectiveness. Therefore, we considered data related to completed projects which have been imputed to the year of completion.

Figure 1 – Quantile of per capita income levels: years 2007 and 2019, respectively



Source: Authors' elaboration

The information on completed projects ranges from 2008 to 2017. This information has been calculated for a sample of 103 Italian provinces[3].

All projects financed through cohesion policies were considered, with a breakdown between European and national cohesion policy. For the first, the resources of the ERDF and the ESF were considered. For the national cohesion policy we took into consideration the projects implemented through the *Fondo di Sviluppo e Coesione* (*FSC, former Fondo Aree Sottoutilizzate*) and by *Piano di Azione e Coesione*[4] (PAC).

A feature of our analysis compared to most existing literature is that the European cohesion variable is constructed as the sum of resources from the ERDF

3. The currently active provinces in Italy as statistical units are 107. However, in this analysis we have excluded those that have undergone transformations or were established during the period in which the analysis is extended. The excluded provinces are Monza and Brianza, Fermo and Barletta-Andria-Trani because they were established in 2004 but became operational in 2009 and, finally, the last province established in Italy: South Sardinia.
4. Active since 2012.

and ESF plus national co-financing by *Fondo di rotazione per l'attuazione delle politiche comunitarie*[5].

Both European and national cohesion variables were expressed in per capita terms following most of the existing literature (see on this point, Coppola *et al*., 2020; Rodrìguez-Pose, Novak, 2013; Rodriguez-Pose, Garcilazo, 2015).

The dependent variable is in our case the logarithmic growth of the provincial per capita GDP expressed in constant terms. We used the three-year average of these values to control for short-run cyclical variations.

All the variables in the explanatory set are calculated in the initial year of the three-year period to reduce the endogeneity problem. In addition to initial level of per capita GDP (to test the beta convergence), this set includes three types of variables.

The first group is composed of policy variables, namely the European cohesion policy (ECP) which includes the national co-financing and the National cohesion policy (NCP). The second group includes relevant variables which may act as control variables since they take into account the specific features of the local economy. In detail, this set includes:

1) Population density (attractiveness index). This variable is potentially suitable for solving the problem of omitted-variable bias, because it is a proxy of urbanization. If an area is more dense, it offers a greater availability of good facilities and infrastructures such as schools, hospitals, local transport etc. by acting, at the same time, as a relevant workplace. We expect a positive role for this variable (Becker *et al*.,1999; Glaeser, 1999). Data came from ISTAT database.

2-3) Public specialization (labour market resilience index) and agricultural specialization (index of vulnerability to exogenous shock). Specialization in public and in agricultural sector was considered to capture the production structure of local economies. We have selected specifically these indicators as more sensitive in a period of economic crisis. Indeed, the specialization in the public sector should improve the resilience in terms of jobs. We therefore expect a positive sign for the coefficient related to this variable. Conversely, the agriculture sector is very vulnerable to exogenous shocks such as climate change, the introduction of sustainable process innovations, international trade (Urruty *et al*., 2016) and so on. We expect a negative sign for the coefficient related to this variable. Both indicators have been calculated using the ISTAT provincial employment series.

4) Trade openness (competitiveness index). Openness to international trade (calculated by trade balance as a percentage of the provincial added value using the ISTAT series) is a proxy of provincial competitiveness. There is agreement in the literature on the propulsive role of internationalization for economic

5. Coppola *et al*. (2020) use this methodology in a study on Italian NUTS-2 regions.

growth (see for instance, Romer, 1990; Harrison, 1996; Frankel, Romer, 1999; Wacziarg, 1999).

5) Graduates (human capital index). The accumulation of human capital, defined as tertiary education rate (30-34 year range) in our analyses, is one of the main determinants of economic development (Mincer, 1981). Data came from ISTAT database.

   The last set of variables includes elements of a composite indicator developed in the literature, and called "territorial capital" (Camagni, 2008; Camagni, 2009). They describe additional local economy characteristics such as infrastructural, natural, relational and social capital.

6) Infrastructural capital. The role of public infrastructure in stimulating economic growth has been much debated and explored among economists (e.g., the works of Aschauer, 1989; Munnel, 1990a, 1990b, 1992). In our work, given the heterogeneity of Italian provinces, we considered the road endowment index calculated by *Istituto Tagliacarne* (see Mazzola *et al*., 2018; Lo Cascio *et al*., 2019).

7-9) Natural, relational and social capital. As proxies for natural, relational and social capital, we examined the available indicators among those proposed by Nifo and Vecchione (2014). For natural capital we considered the urban green space per inhabitant (data from ISTAT). Relational capital was proxied by the weight of cooperatives on total employees (data from ISTAT) Finally, for social capital (behavioral models, values, reputation) we selected a crime indicator (denounced crimes per 100.000 inhabitants, available in the ISTAT database). We expected a positive coefficient for the proxies of natural and relational capital and a negative coefficient for the proxy of social capital.

To take into account the potential impact of the Great Recession on cohesion policies' effectiveness, we inserted two dummy variables capturing the interaction between crisis years and cohesion policy variables[6]. The ex-ante impact of the Great Recession is ambiguous since Structural Funds may have acted positively in favouring the resilience of some local economies. Instead, in case of negative sign, the occurrence of a severe global downturn would be associated with a slowdown in Funds' effectiveness.

4.2. Econometric Strategy

Given the potential relevance of the spatial spillovers in evaluating public policies outcomes, even more at a sub-regional level, we employ the Spatial

6. The first dummy is the interaction between European Funds and the crisis years (2008-2009-2010-2011-2012), the other is the interaction between national cohesion funds and the same years.

Autoregressive Model (SAR, Equation 1). When the spatial independence hypothesis between the observations cannot be assumed, the derivative of y_i with respect to x_{ik} is not β_k since the explanatory variable k influences the i-th unit (direct effect), but also the j-th unit (indirect or spillover effect) and there may also be a feedback effect towards the i-th area (LeSage, Pace, 2009).

$$Y_{it} = \alpha + \sum_{(k=1)}^{K} x_{itk}\beta_k + \rho\sum_{(j=1)}^{N} w_{ij} y_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \qquad [1]$$

$$i = 1,\dots,N \qquad t = 1,\dots,T$$

The coefficients w_{ij} take into account the spatial structure of the data as elements of the spatial matrix of the distances (W). We used a NxN non-negative and non-stochastic binary queen-contiguity matrix:

$$W = \begin{cases} w_{i,j} = 0 & if \quad i = j \\ w_{i,j} = 1 & if \quad d_{i,j} = 0 \end{cases} \qquad [2]$$

The spatial weights were normalized in order to have the sum of each row equal to one (row normalization):

$$\sum_{(j=1)}^{n} w_{ij} = 1 \qquad [3]$$

$$i = 1,\dots,n$$

where ρ is the coefficient which quantifies the degree of spatial dependence between the growth of the i-th unit and the other territorial areas since the spatial proximity is likely to lead to similar growth paths (Anselin, Bera, 1988).

Mathematically (Belotti *et al*., 2017), the SAR model computes direct and indirect spillover effects as follows:

SAR direct effects	SAR indirect effects
$\{(I - \rho W)^{-1} \times (\beta_k I)\}^{d}$	$\{(I - \rho W)^{-1} \times (\beta_k I)\}^{rsum}$

where d is the operator that calculates the mean diagonal element of the matrix and *rsum* is the operator that calculates the mean row sum of the nondiagonal elements.

A peculiarity of the direct effect is the inclusion of feedback, i.e., the effect of X_i on j affects, in turn, *again i.* As we can see from the formula of the direct effect reported above, feedback is due to the coefficient of the spatially lagged dependent variable. The inclusion of feedbacks in the direct effects may generate discrepancies between impact coefficients (β›*s*) and direct ones.

We added fixed effects according to the result of Hausman tests and following the consolidated literature (to name one, Wooldridge, 2009) which asserts that the fixed effects are more appropriate to control for unobserved territorial-specific factors, in particular when the regional sample covers the entire national population, as in our case.

Table 1 – Estimations Results of SAR-FE Model (2008-2017) – European Cohesion Policy Impact

Variables	*Impact effects*	*Direct effects*	*Indirect effects*	*Total effects*
Wy	0.4126 *** (16.81)			
GDPpc	-73.6929*** (-25.45)	-77.4488*** (-26.35)	-48.0846*** (-11.56)	-125.5335*** (-23.03)
EU Cohesion Policy (ECP)	0.0124*** (5.30)	0.0130*** (5.45)	0.0080*** (5.29)	0.0210*** (5.54)
Crisis years*ECP	-0.0185*** (-4.76)	-0.0191*** (-4.91)	-0.0118*** (-4.84)	-0.0309*** (-5.01)
Population Density (Attractiveness)	20.9755*** (3.37)	21.9440*** (3.45)	13.6094*** (3.35)	35.5535*** (3.45)
Public Specialization (Resilience)	1.0862** (5.80)	1.1502*** (5.88)	0.7154*** (5.02)	1.8657*** (5.68)
Agricultural Specialization (Vulnerability)	-0.2743 (-1.39)	-0.2753 (-1.32)	-0.1695 (-1.32)	-0.4449 (-1.32)
Trade Openness (Competitiveness)	0.0718*** (4.00)	0.0756*** (3.87)	0.0469*** (3.72)	0.1226*** (3.87)
Human Capital	0.1837*** (5.24)	0.1929*** (5.26)	0.1195*** (5.05)	0.3124*** (5.31)
N.obs	824			
R2	0.6746			
Hausman test	236.90			

Note: Robust t-test in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.10.
Source: Authors' elaboration

5. Results

Tables 1 and 2 show the results of the models with the first and the second groups of variables only, thus excluding territorial capital elements. Table 1 reports the model specification evaluating the effects of the European cohesion policy. European projects are statistically relevant for growth of both the treated provinces and the neighbouring ones, but they display relevant spatial spillover effects. However, the policy effectiveness on the treated areas does not depend exclusively on the spillovers.

The coefficient of the spatially lagged dependent variable (*Wy*) is positive and statistically important, demonstrating that the growth path of the Italian provinces is connected with the economic growth of neighbouring.

Table 2 – Estimations Results of SAR-FE Model (2008-2017) – National Cohesion Policy Impact

Variables	*Impact effects*	*Direct effects*	*Indirect effects*	*Total effects*
Wy	0.4498***			
	(19.21)			
GDPpc	-69.2200***	-73.5642***	-52.2510***	-125.8153***
	(-24.45)	(-25.19)	(-11.94)	(-21.55)
National Cohesion Policy (NCP)	0.0432***	0.0456***	0.0323***	0.0780***
	(5.31)	(5.50)	(5.24)	(5.52)
Crisis years*NCP	-0.0423***	-0.0436***	-0.0309***	-0.0746***
	(-3.62)	(-3.66)	(-3.59)	(-3.68)
Population Density (Attractiveness)	18.5054***	19.5994***	13.9051***	33.5045***
	(2.96)	(3.02)	(2.97)	(3.02)
Public Specialization (Resilience)	1.2035***	1.2864***	0.9145***	2.2009***
	(6.44)	(6.59)	(5.67)	(6.38)
Agricultural Specialization (Vulnerability)	-0.1750	-0.1716	-0.1206	-0.2923
	(-0.89)	(-0.82)	(-0.81)	(-0.81)
Trade Openness (Competitiveness)	0.0787***	0.0837***	0.0594***	0.1432***
	(4.36)	(4.23)	(4.09)	(4.24)
Human Capital	0.1947***	0.2062***	0.1461***	0.3524***
	(5.50)	(5.50)	(5.34)	(5.57)
N.obs	824			
R2	0.6611			
Hausman test	165.52			

Note: Robust t-test in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.10.
Source: Authors' elaboration

The same result in terms of direct and indirect impact is obtained for national cohesion projects (Table 2). In this case the impact is stronger than in the case of European cohesion policies for all types of effects. During the Great Recession years, the impact of the two policies as well as spillover effects have drastically reduced. Therefore, the economic crisis has slowed down the action of Structural and Investment Funds but have not completely eliminated their (positive) effects.

The signs and significance of the estimated coefficients of the other explanatory variables are all consistent with economic theory and prior hypotheses. In particular, the attractiveness, as population density, and the competitiveness, as trade openness, of the *i*-th economy is positive for the growth of the same unit but also for neighbouring areas, thus exerting spatial spillovers.

The two specialization variables partially confirm the initially assumptions: the stability of public employment is a relevant factor for growth, while the specialization in the agricultural sector is negative though not statistically significant.

Table 3 – Estimations Results of SAR-FE Extended Model (2008-2017) – European Cohesion Policy Impact

Variables	*Impact effects*	*Direct effects*	*Indirect effects*	*Total effects*
Wy	0.3768*** (14.84)			
GDPpc	-74.8514*** (-26.25)	-77.8812*** (-26.99)	-41.8482*** (-10.64)	-119.7295*** (-23.30)
EU Cohesion Policy (ECP)	0.0119*** (5.19)	0.0123*** (5.31)	0.0066*** (4.93)	0.0190*** (5.33)
Crisis years*ECP	-0.0176*** (-4.57)	-0.0179*** (-4.69)	-0.0096*** (-4.49)	-0.0276*** (-4.73)
Population Density (Attractiveness)	15.7137*** (2.48)	16.2102*** (2.53)	8.7178*** (2.44)	24.9280*** (2.52)
Public Specialization (Resilience)	1.0271*** (5.53)	1.0770*** (5.60)	0.5800*** (4.73)	1.6570*** (5.41)
Agricultural Specialization (Vulnerability)	-0.3217 (-1.64)	-0.3218 (-1.56)	-0.1707 (-1.56)	-0.4926 (-1.57)
Trade Openness (Competitiveness)	0.0768*** (4.37)	0.0802*** (4.23)	0.0430*** (4.02)	0.1233*** (4.23)
Human Capital	0.2044*** (5.89)	0.2125*** (5.93)	0.1139*** (5.64)	0.3264*** (6.06)
Infrastructural Capital	0.0471* (1.76)	0.0516* (1.89)	0.0276* (1.87)	0.0793* (1.89)
Natural Capital	0.2621*** (3.29)	0.2748*** (3.30)	0.1477*** (3.15)	0.4226*** (3.28)
Relational Capital	0.3327 (1.13)	0.3460 (1.15)	0.1843 (1.12)	0.5304 (1.14)
Social Capital	-0.3212*** (-5.49)	-0.3317*** (-5.36)	-0.1772*** (-5.66)	-0.5090*** (-5.64)
N.obs	824			
R^2	0.7046			
Hausman test	215.62			

Note: Robust t-test in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.10.
Source: Authors' elaboration

Local economies with high levels of human capital tend to cluster since the tertiary education rate is important both as a direct effect and as an indirect one.

Our results are robust to the inclusion of the additional set of territorial capital elements (see Tables 3 and 4), European and national cohesion projects have a positive and statistically significant impact on the provincial per capita GDP growth and spillovers maintain relevance.

Table 4 – Estimations Results of SAR-FE Extended Model (2008-2017) – National Cohesion Policy Impact

Variables	*Impact effects*	*Direct effects*	*Indirect effects*	*Total effects*
Wy	0.4080*** (16.59)			
GDPpc	-70.5169*** (-25.28)	-73.9602*** (-25.89)	-44.6959*** (-10.93)	-118.6562*** (-21.81)
National Cohesion Policy (NCP)	0.0408*** (5.13)	0.0425*** (5.29)	0.0257*** (4.85)	0.0683*** (5.25)
Crisis years*NCP	-0.0382*** (-3.32)	-0.0388*** (-3.34)	-0.0234*** (-3.21)	-0.0623*** (-3.33)
Population Density (Attractiveness)	11.9106* (1.88)	12.3972* (1.91)	7.5019* (1.87)	19.8991* (1.90)
Public Specialization (Resilience)	1.1339*** (6.11)	1.1965*** (6.25)	0.7241*** (5.28)	1.9207*** (6.03)
Agricultural Specialization (Vulnerability)	-0.2178 (-1.11)	-0.2140 (-1.03)	-0.1271 (-1.02)	-0.3412 (-1.03)
Trade Openness (Competitiveness)	0.0839*** (4.74)	0.0881*** (4.60)	0.0531*** (4.38)	0.1413*** (4.61)
Human Capital	0.2167*** (6.20)	0.2266*** (6.20)	0.1366*** (5.95)	0.3633*** (6.35)
Infrastructural Capital	0.0558** (2.06)	0.0610** (2.20)	0.0368** (2.17)	0.0978** (2.20)
Natural Capital	0.2104*** (2.63)	0.2235*** (2.66)	0.1352*** (2.58)	0.3587*** (2.65)
Relational Capital	0.4834 (1.62)	0.5071* (1.65)	0.3042 (1.63)	0.8113* (1.65)
Social Capital	-0.3426*** (-5.83)	-0.3564*** (-5.66)	-0.2142*** (-6.00)	-0.5707*** (-5.99)
N.obs	824			
R2	0.6969			
Hausman test	208.43			

Note: Robust t-test in parentheses. ***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.10

Source: Authors' elaboration

The gains from infrastructural adequacy are captured both by the same areas and by neighbouring ones, a result that confirms that Italian territories are linked by tight social and economic relations.

As for more softer indicators, it appears that, as expected, a high crime rate is harmful for economic growth while the positive role of natural capital is confirmed. The association and cooperation attitude seems to have a marginal role on growth.

6. Conclusions

Our work evaluated the economic effects of the completed projects under the European and national cohesion policies by stressing the role of spatial interactions. During the last two programming periods before the current one (2007-2013 and 2014-2020), the European and national regional policy have affected positively the economic growth of the Italian provinces. Through the estimation of a SAR spatial panel model, we found that the action of spatial proximity was clear. It gave additional impulse to the effectiveness of regional policies in the *directly treated areas* since we found a positive and statistically impact both on the direct and indirect effects. However, from this analysis it appears that the funds' impact *has not been completely mediated* by spatial interactions as no displacement effects occurred. We also found that the national cohesion policy had a greater effect on Italian NUTS-3 regions' growth compared to European regional policy. Finally, the Great Recession has reduced the effectiveness of cohesion policy on economic growth in both direct and indirect (spillover) effects.

These conclusions drive some considerations concerning the need to assess policy intervention impact at both local and wider territorial levels. We may also infer that policy efforts should be directed towards projects with higher potential to generate positive spillovers. In addition, our results stress the importance of integrating cohesion policies coming from both national and supra-national institutions to obtain greater effectiveness and of reinforcing support for lagging areas during severe downturns.

Further investigation on these results may consider the evaluation of the role of spatial spillovers for the effectiveness of concluded cohesion projects at a more aggregated level of analyses (NUTS-2 territories). In addition, our research agenda includes the comparison of the results of this analysis with those originated by the application of other spatial methodologies or different measures of cohesion interventions.

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Il ruolo degli spillover spaziali per l'efficacia della Politica Regionale: un'analisi panel spaziale per le province italiane

Sommario

Il presente lavoro valuta l'impatto degli spillover spaziali sull'efficacia dei progetti finanziati dalla Politica di Coesione europea e nazionale nelle province italiane (NUTS-3) durante i periodi di programmazione 2007-2013 e 2014-20. La ricaduta degli effetti economici di un intervento pubblico al di fuori delle aree direttamente trattate è certamente auspicabile. Tuttavia, ciò può generare un effetto di spiazzamento quando la politica risulta maggiormente efficace nei territori limitrofi. La nostra strategia econometrica in panel tiene conto del pattern di autocorrelazione spaziale tra le province adiacenti attraverso la stima di un modello panel spaziale. Dall'impatto totale delle politiche, distinguiamo quello diretto sulla crescita del PIL pro-capite delle province trattate e quello indiretto di spillover. Il lavoro esamina anche l'eventuale variazione dell'impatto delle politiche e della direzione degli spillover nel periodo della Grande Recessione valutando se la Politica Regionale abbia agito come fattore di resilienza nelle economie locali. Il dataset è stato ricostruito dal database Opencoesione e contiene, per la prima volta in letteratura, le spese registrate relative ai progetti completati. I principali risultati dell'analisi mostrano che, durante il periodo considerato, gli spillover spaziali tra le province italiane hanno avuto un impatto positivo per l'efficacia della Politica di Coesione europea e nazionale, in aggiunta agli effetti diretti sulle aree trattate. Negli anni della crisi, gli spillover si sono drasticamente ridotti.

Do Spatial Spillovers of Regional Policies Aid the Reduction of Regional Inequalities in Europe?

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Abstract

The European cohesion policy promotes the harmonious development of the Union and its regions, fostering inclusive growth and employment in less developed regions, improving people's well-being and reducing regional disparities. However, the effects of the policy are both direct, in the regions where the policy has been addressed, and indirect, in neighboring or economically connected regions through the generation of spillovers. Evaluating the total effects of these policies is therefore complex, as both direct effects and spillovers must be considered. However, spillovers are generally excluded from the classic counterfactual model, which does not allow for interference effects between treated and untreated units of the policy (named SUTVA – Stable Unit Treatment Assumption – assumption). This work aims to overcome this restriction, by implementing a methodology fully coherent with the counterfactual approach but relaxing this assumption. We propose a spatial difference-in-differences model, based on the Spatial Durbin Model (SDM) specification that allows for spillover effects. The paper evaluates the total effects of regional policy of the programming period 2007-2013. Results show positive effects of European regional policy especially in the Eastern regions, where the policy produces high positive externalities, reducing inequalities with the more developed regions.

1. Introduction

The size of regional disparities within Europe is strongly heterogeneous across space. Some regions, such as clusters of Western Europe, tend to be economically developed, while others, such as clusters of Eastern Europe, have traditionally been less developed. Within individual countries, there are also often significant

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disparities between different regions. One major factor contributing to regional disparities is the uneven distribution of economic growth and wealth across the region (Agnew, 2001). This has led to persistent differences in standards of living, levels of education, and access to economic opportunities.

The strategy for reducing regional disparities in Europe is based on the European Union's (EU) regional development policies. European regional policy is the world most important place-based policy, designed to promote economic development and reduce disparities between regions (Ertur *et al.*, 2006; Vedrine *et al.,* 2021) within the European Union (EU), redistributing resources and funding from more developed regions to those lagging behind.

The set of policy measures can take many forms, such as infrastructure investment, business support programs, and regional financing instruments. Although there has been a long debate on the effects of European regional policy, from a theoretical as well as empirical viewpoint (e.g., Venables, Duranton, 2019; Ehrlich, Overman, 2020), evaluative studies adopting robust counterfactual methodologies and the dataset shared by the commission clearly show the occurrence of a positive impact on economic development and the reduction of regional disparities, although the size of these impacts is heterogeneous in space and time. There are several papers on this, such as Becker *et al*., (2010); Pellegrini *et al*., (2013), which show that average income and employment grow more in heavily subsidized areas. At the same time, the EU regional policy is heterogeneous, in terms of both the intensity of treatment as well as the combination of the different policy instruments, and the debate on what is the optimal amount and the optimal combination of the different types of programs is still in progress (e.g., Rodríguez-Pose, Garcilazo, 2015; Bachtrögler *et al*., 2019; Di Caro, Fratesi, 2022; Cerqua, Pellegrini, 2022). A new approach, which confirms previous findings, is the one that analyses what happens when regional policy support ends. Cerqua and Pellegrini (2022) investigate what happens when strongly subsidized regions experience a substantial reduction in funding. The results indicate that only regions that experienced a considerable reduction in funding during a recession suffered a negative impact on economic growth. Overall, the regions that left the convergence status appear to have survived this shock relatively well, suggesting a long-term positive impact of the EU regional policy.

In the evaluation of place-based policies, evaluators should keep in mind that one of the founding rationales of such programs very often consists in generating positive externalities, such as a general improvement of the eligible areas' socio-economic situation (Cerqua, Pellegrini, 2014). This is particularly true where less developed regions are grouped into geographic clusters, and therefore the effects of policies are both direct, in the regions beneficiaries of the policy, and indirect, in neighbouring or economically connected regions through the generation of spillovers. Spillovers refer to the effects that a policy or intervention has on areas beyond those directly targeted. In the context of European regional policy, spillovers refer to the effects that a policy has on regions beyond those directly receiving support. However, spillover effects on neighboring regions can be positive or negative (De Castris, Pellegrini, 2012), depending on several factors, for instance on the specific measures implemented and the context in which they are implemented. The overall effect of the policy therefore includes the complete set of impacts on the territory, both internal and external to the objective of the policies themselves.

The evaluation of the total effects of regional policies is therefore complex, as it is necessary to consider and estimate the size and sign of spillovers. Considering regional spillovers is important for several reasons. First, spillovers have significant impacts on the development and well-being of neighbouring regions, and it is important to evaluate these impacts to assess the overall effectiveness of a regional policy. Second, spillovers are an important factor in policy design, as policymakers may wish to consider the potential impacts of a policy on neighbouring regions when deciding whether to implement it. Finally, understanding spillovers helps policymakers to identify potential unintended consequences of a policy and eventually to design measures to mitigate negative spillovers.

A further difficulty is that spillovers are generally excluded from the classic counterfactual model by Rubin, which does not allow for interference effects between treated and untreated units of the policy (named SUTVA assumption). In this paper we have chosen to remain within the counterfactual approach, and to estimate the spillovers implementing a methodology fully consistent with this approach. The spillovers considered depend on the spatial distance and are estimated based on a model with a spatial specification of the Spatial Durbin Model (SDM) type. We propose a spatial difference-in-difference (DiD) model, that allows for spillover effects. The total effects are decomposed in direct and indirect effects, following the approach presented in LeSage and Pace (2009) and Arbia *et al*. (2020). The paper evaluates the total effects of regional policy of the programming period 2007-2013 using data at both Nuts-2 and Nuts-3 level. Results show overall positive effects of European regional policy, especially in the Eastern regions, where the policy produces high positive externalities and reduce inequalities with the more developed regions.

Our work contributes to the literature on policy evaluation in the presence of spillovers. The applied econometrics literature has shown that spillovers can lead to biased estimates if they are not properly accounted for. For example, Kalenkoski and Lacombe (2013) demonstrate that analyses of minimum wage changes, like the influential work of Card and Krueger (1994), can suffer from bias when spillovers are ignored, especially when contiguous counties are selected as controls due to spatial heterogeneous trends, as in Dube *et al*. (2010) and Neumark and Kolko (2010).

Hanson and Rohlin (2013) show how using nearby areas as controls to evaluate policies, as analysed for de-regulation policies for labour in Holmes (1998), banking in Huang (2008), and crime prevention in Blattman *et al*. (2017), can present upward biases when spillovers are negative (see also Cerqua, Pellegrini, 2014). This study contributes to the literature by proposing a spatial region-level regression design to control for spillover effects exploiting geographic proximity. Our analysis provides measures of both the spillover and the direct effect net of the spillover bias, allowing for an assessment of the overall effectiveness of a regional policy.

2. Regional Policy and Spillover Effects

A large body of literature evaluated the effectiveness of Structural Funds to reduce economic and social inequalities. As reported by Ehrlich and Overman (2020), many studies (Becker *et al*., 2010; Mohl, Hagen 2010; Pellegrini *et al*. 2013; Giua, 2017) demonstrate that on average, Cohesion Policies appear to have been effective in reducing disparities. This effect depends on the policy impact on beneficiaries and on indirect effects caused by economic interactions between regions. Indeed, one relevant feature of cohesion policy is that its structural investments can generate substantial spatial spillovers (Di Gennaro, Pellegrini, 2019; Fratesi, 2020; Monfort, Salotti 2021). Spatial spillovers imply that the economic impact of the policy is not confined to the target regions, but spills over to the rest of the EU (Monfort *et al*, 2021).

In the context of regional policy, spillover effects occur because policy implemented in one region has an impact, which can be positive or negative, on the economic or social conditions of neighboring regions. Positive spillover effects can occur when a regional policy leads to economic growth or improved social conditions in the recipient region, which can then spill over to neighboring regions through increased trade or other economic linkages. Negative spillover effects can occur when a regional policy leads to negative economic or social consequences in the recipient region, which can then spill over to neighboring regions. Overall, the size and direction of spillover effects will depend on the specific policy being implemented, the characteristics of the recipient region, and the economic and social linkages between the recipient region and neighbouring regions.

In general, the impact of regional policy on neighbouring regions will depend on a variety of factors, including the specific policies being implemented, the economic, social, and environmental characteristics of the regions involved, and the extent to which the regions are integrated and interconnected (Capello, 2020; Cerqua, Pellegrini, 2020).

Angelucci and Di Maro (2016) identify four types of spillover effects: (1) externalities, where effects operate from the treated subjects to the untreated population. An example is an increase in the local demand that spread out in the neighboring regions (2) general equilibrium effects, i.e. effects that an intervention, which targets only part of the local economy, can have on the entire population. An example is an investment policy that affect the price of the investment goods (3) interactions, where the local nontarget population may also be indirectly affected by the treatment through any social and economic interaction with the treated. A classical example is the distribution of classbooks, that can be used also by non-treated individuals and (4) behavioural effects. These spillover effects stem from an intervention that affects the behavioural or social norms within the contexts (say a locality) in which these interactions are relevant.

Among the regional policies, investment subsidies policies have also been particularly studied in its spillover effects. Cerqua and Pellegrini (2017) highlight that investment subsidies policies are a way to trigger endogenous changes and generate a self-sustaining growth. Therefore, business incentives policies are not only expected to improve the economic situation of subsidized firms but also to generate a virtuous circle that will benefit unsubsidized firms. However, business incentives programs can potentially generate also negative spillovers. In the literature, the most quoted negative spillover is arguably the cross-sectional substitution (Cerqua and Pellegrini, 2017). This externality occurs when subsidized firms take some of the investment opportunities that unsubsidized firms would have exploited in the absence of the policy. In presence of cross-sectional substitution, publicly funded investments partially crowd-out private investments making the rationale in favour of business incentives less clear. Thus, the assessment of the net effect of the policy is an empirical problem, to be evaluated by means of suitable econometric analysis.

3. Methodology

An important methodological aspect for policy evaluation analyses concerns the treatment of the presence of interference (spillovers) among units, both treated and untreated. In the Rubin casual model, the SUTVA formalizes the absence of interference among units. This implies that spillover effects are ruled out by this assumption. Cerqua and Pellegrini (2019) highlight that "although many public policies can be credibly evaluated under the SUTVA, this is rarely valid for the evaluation of regional policies, as we should expect them to engender spillover effects". Only in the case of the absence of interference the non-treated subjects, whether people or geographical areas, are valid control samples, or the counterfactual, of what would have happened to the treated without treatment.

However, the Stable Unit Treatment Value Assumption (SUTVA) appears completely unrealistic in many evaluations of regional policies, like the European regional policy, which often have the purpose of generating spillovers between treated and untreated units to engender local development. In our case, the possibility of interference is higher, because the target population is a subset of the regional economy, loosely defined as the geographic unit or local institution within which the target population lives and operates (Angelucci, Di Maro, 2016). To design an evaluation strategy that accounts for the presence of spillover effects requires understanding and identification of which untreated units are subject to spillovers. In our paper we assume that the presence of interference depends directly on the geographical distance. This is a common assumption, which constrain the effects of spillover to follow a certain spatial pattern. This approach is at the basis of spatial econometric models (see, among others, Anselin 2003; Arbia, 2014), which use a spatial weight matrix to model the interactions between units.[1] However, identification of spillover effects is closely related to the analytical tools used and in particular to the spatial econometric models identified (Arbia *et al*, 2020; Delgado, Florax, 2015) that justify interference effects with the relationships between regions.

In this paper we apply a methodology useful to identify, estimate and disentangle spatial effects of the policy, both direct and indirect. In a counterfactual framework, we use a modified spatial difference-in-differences estimator (Di Gennaro, Pellegrini, 2016). The idea is to highlight the spatial effects due to the policy treatment and, in overall, to provide unbiased estimates of the effects of the policies. The pillar of the empirical methodology is a spatial autoregressive Durbin model (SDM) combined with a difference-in-differences (DiD) estimator.

In the standard counterfactual approach, under SUTVA and common trend assumptions (Lechner, 2011) a DiD model is applied by using an interaction term between time and treatment indicator whose coefficient describes the difference over time in the outcome variable between the treated and untreated groups.

Let recall the DiD model:

$$Y = \beta_0 + D\beta_1 + t\beta_2 + D't\beta_3 + \varepsilon \qquad [1]$$

Where Y is the n x1 vector of dependent variable, in our paper the growth rate of the outcome variable in the pre-post period treatment, t is the n x1 vector of time dummy variable that assumes value 0 in the pre-treatment time and value 1 in the post-treatment, D is the n x1 vector of treatment dummy variable, and ε is the n x 1 vector of regression disturbance terms.

In presence of interferences, the casual framework changes to consider a different number of potential outcomes, i.e., the effect of the treatment with and without

1. Although the approach to place more weight on closer observations is widely accepted, the true spatial matrix is generally unknown (Halleck-Vega, Elhorst, 2015). Moreover, in some applications even relatively small perturbations in the spatial weights matrix will have salient consequences in the empirical results (Ward, Gleditsch, 2008).

interactions. We introduce a proximity function based on the state of treatment of the neighbours, imposing the restriction to consider only the first level of proximity.

We consider the spatial econometrics model that contains parameters that allow for the incorporation of spatial dependence among the observations. These parameters include spatial lag and error terms, which capture the relationship between the dependent variable and its neighbours, as well as spatial weights matrices, which specify the strength of the relationship between the observations.

Starting from the founding model by Manski (1993):

$$Y = \rho WY + X\beta + WX\theta + u \qquad [2]$$
$$u = \lambda Wu + \varepsilon$$

where β is the vector of parameters for exogenous explanatory variables in vector X, ρ is the spatial autoregressive parameter for the endogenous interaction effect, θ is the parameter for exogenous interaction effects (of dimension equal to the number of exogenous variables) and λ is the spatial autocorrelation parameter (spatial effect of errors).

Following Elhorst (2010) classification models, we can assume the case $\rho = 0$ that makes explicit the hypothesis that there is no endogenous interaction and so the accent is placed on neighbourhood externalities, i.e., spillover effects. The model under consideration with the restriction is named Spatial Durbin Error Model (SDEM)

$$Y = X\beta + WX\theta + u \qquad [3]$$
$$u = \lambda Wu + \varepsilon$$

the model analyses the relationships between Y and one or more independent variables X, while taking into account the spatial dependence between the units.

In contrast, if we assume that the model is such that $\lambda = 0$,

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \qquad [4]$$

known as the Spatial Durbin Model (SDM), the model assumes that the value of the dependent variable for a given unit is not only influenced by the values of the independent variables for that unit, but also by the values of the dependent variable for neighbouring units.

Moreover, it is important to consider the potential bias induced by the fact that observation units belong to groups, like considering provincial data in analysing public funds provided at regional level. In fact, regardless of the presence of spatial autocorrelation, the independence assumption is usually erroneous when data are extracted from a population with a clustered structure, since this adds a common element to the errors thus inducing correlated errors within the group (Corrado, Fingleton, 2011). We know it is necessary to account for clustering either in the error term or in the specification of regressors (Moulton,1986). For example, this can occur when we consider administrative areas, like regions and provinces, where neighboring areas may have greater similarity with respect to the farthest ones. One way to incorporate the group effect is to assess the impact on the singular unit of higher-level variables that measure one or more aspects of the composition of the group. In order to control for structural differences between areas, i.e. clusters characterized by, for example, exceptionally high, or low, economic growth, in our work we model specific dummy variables designed for properly asses unobservable spatial effects that, if not accounted, could produce biased estimation of the impact of the policy considered.

4. Empirical Strategy

We focus on a known "microlevel" difference-in-differences (DiD) model in which the treatment is assigned to a group (Nuts-2 region) and observations are available also for units within groups (Nuts-3 unit) before and after the intervention.

$$\Delta Y_{prt} = \beta_0 + \beta_1 D_r + \beta_2 t + \beta_3 D_r t + \varepsilon_{prt} \qquad [5]$$

where p indexes province, r indexes regions, t indexes time.

ΔY_{prt} is the GDP growth rate, D is a treatment dummy variable, equals to 1 if the region was treated, but declined at Nuts-3 level, t is a time dummy variable, equals to 0 if 2004-2006 and equals to 1 if 2015-2017, ε_{prt} is the random error term. We are in the simplest case, in which there are only two groups, i.e., treated and control, without spillover.

To account for initial differences between regions and spillover effects from neighbouring regions, we modify the model by introducing variables that can control for heterogeneous effects and spatial effects.

Let define:

- a spatial weights matrix W, an $p \times p \times 2$ positive symmetric matrix with element w_{ij}, each one is a weight for each pair of locations (i, j). The spatial matrix represents the spatial structure (Kelejian, Prucha, 1998; 2010) of our data where p is the number of Nuts-3 units, equal to 1320;
- an indicator D_j representing the presence of neighbours treated units, given by the spatial lag of the treatment variable at the Nuts-3 level;
- a set of covariates X describing the socioeconomic heterogeneity within regions, by means of the provincial-level variables, which are population growth rate and manufacturing employment growth rate;

- dummy variables to capture fixed effects: Eu enlargement as 2004 and 2007, capital city, metropolitan areas, pre-treatment clusters of more or less, resp. performing regions.

  Let's get the integrated model:

$$\begin{aligned}\Delta Y_{prt} = {} & \beta_0 + \beta_1 D_r + \beta_2 t + \beta_3 D_r t + \beta_4 D_j D_r \\ & + \beta_5 D_j t + \beta_6 D_j D_r t + \beta_7 \Delta X_{pt} + \beta_8 \mu_p + \varepsilon_{pr}\end{aligned} \qquad [6]$$

Introducing the Spatial Durbin error model, we combine both a spatial autoregressive and a spatial error component as:

$$\begin{aligned}\Delta Y_{pr} = {} & \rho W \Delta Y_{pr} + \beta_0 + \beta_1 D_r + \beta_2 t + \beta_3 D_r t + \beta_4 D_j D_r \\ & + \beta_5 D_j t + \beta_6 D_j D_r t + \beta_7 \Delta X_{pt} + \beta_8 \mu_p + \varepsilon_{pr}\end{aligned} \qquad [7]$$

where the spatial autoregressive parameter, ρ, refers to the endogenous spatial lag While the structure of the error is:

$$u_{pr} = \lambda W u_{pr} + \varepsilon_{pr} \qquad [8]$$

We estimate both the case with $\rho = 0$ (there is no endogenous interaction) and the case with λ=0 (no spatial dependence between the units).

5. Data

We make use of an integrated dataset, which combines data by different sources, linking, at both Nuts-2 and Nuts-3 level, data on economic and demographic variables.

Data on economic and demographic variables (population growth, manufacturing employment growth) comes from European Regional Database of Cambridge Econometrics that contains annual observations since 1980 at Nuts-3 level, while the GDP growth rate comes from Eurostat Regional Database that contains annual observations at Nuts-3 level.

We consider data for both the pre-treatment and post-treatment periods. The pre-treatment period refers to the years 2004-2006, the treatment period is 2007-2013, and the post-treatment period includes information between 2015 and 2017, also to consider the closing period of the 2007-2013 policy cycle.

Some characteristics of the sample before and after the policy by full sample, Eu15 regions, Eastern Europe Enlargement regions, spatial clusters are described in Tables 1 and 2.

Regional population dynamics is very heterogeneous: population growth rates (Nuts-3) ranging from a minimum value of minus 5 percent to a maximum and positive value of 10 percent. On average, enlargement regions before 2007

Table 1 – Summary Statistics of Socioeconomic Indicators Considering the Full Sample, Eu15 Regions, Eastern Europe Enlargement Regions and Distinguishing Between Pre- and Post-Treatment Periods

Indicator A: Population Growth Rate (Nuts-3)

Pre-treatment	*Mean*	*SD*	*Min*	*Max*
Full sample	0.00	0.02	-0.05	0.10
EU15 regions	0.01	0.02	-0.05	0.10
Enlargement regions	-0.01	0.01	-0.05	0.03
Post-treatment	*Mean*	*SD*	*Min*	*Max*
Full sample	0.00	0.01	-0.05	0.07
EU15 regions	0.01	0.01	-0.04	0.05
Enlargement regions	-0.01	0.02	-0.05	0.07

Indicator B: Manufacturing Employment Growth Rate (Nuts-3)

Pre-treatment	*Mean*	*SD*	*Min*	*Max*
Full sample	-0.01	0.07	-0.28	0.41
EU15 regions	-0.02	0.06	-0.28	0.34
Enlargement regions	0.02	0.11	-0.28	0.41
Post-treatment	*Mean*	*SD*	*Min*	*Max*
Full sample	0.02	0.07	-0.36	1.14
EU15 regions	0.01	0.06	-0.36	1.14
Enlargement regions	0.04	0.09	-0.36	0.29

Source: Authors' elaboration

Table 2 – Summary Statistics of Outcome Variable in the Pre-treatment Period: GDP Growth Rate (Nuts-3)

Pre-treatment	*Mean*	*SD*	*Min*	*Max*
Full sample	0,055	0,054	-0,237	0,502
EU15 regions	0,048	0,045	-0,237	0,502
Enlargement regions	0,094	0,078	-0,113	0,418
High-High cluster	0,141	0,060	0,070	0,418
Low-Low cluster	0,001	0,033	-0,237	0,035

Source: Authors' elaboration

register a negative population change of 1 percent. After the policy, while, on average, regional population dynamics remain unchanged, changes are observed in the maximum values, which fall for the full sample and the EU15 countries but rise in the enlargement countries, where a few regions stand out from the average with a growth rate of 7 percent.

Manufacturing employment shows growth trends in all three areas under review, but certainly the enlargement regions, where investment in private and public capital is large, show a higher growth rate.

We define some other dummy variables to distinguish the effect for the new entrant regions (wave of 2004 and 2007), dummies to detect the presence of the capital, the metropolitan areas. In addition, to consider the presence of areas already funded in the previous programming period, i.e., 2000-2006, we control for territories which shifted their treatment status, in particular the ones which switched from beneficiaries to not beneficiaries.

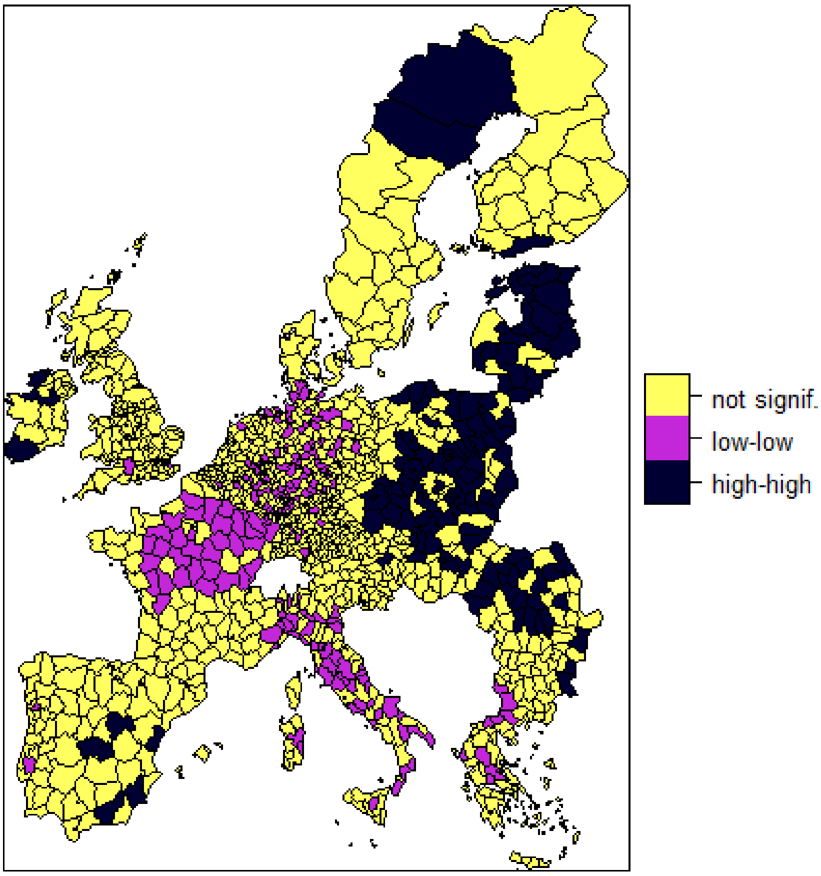
These starting conditions that characterize the regions are introduced in the estimation models, to be consistent with the parallel trend assumption. In our case, the impact of European regional policy, estimated with a selection model on unobservables (DiD), must consider that the new member countries are composed mainly of regions treated with higher growth rates if compared with the rest of the union. This aspect undermines the assumption of common trends and requires an in-depth investigation, based on the presence of cluster of regions with different growth trends.

We test the presence of spatial autocorrelation in the distribution of the outcome variable. The value of Global Moran's I, positive and significant (0.13 with a p-value<0.001), shows that spatial distribution of high values and that of low values in the sample is spatially clustered; it means that high values cluster near other high values and low values cluster near other low values. This assumption is tested by apply a Local Moran's I (Figure 1). Therefore, in the estimation model, the effect due to the presence of hot spots, i.e., high-high value cluster that are composed mainly by treated regions from the enlargement areas has been isolated. At the same time, we highlight cold-spots, i.e., low-low value cluster, characterized by negative, or very low, economic growth. Specific dummies are be added to the model. We built a dataset covering 1310 provinces (Nuts-3) for two periods, for a total number of 2620 observations.

6. Results

We estimate the effect of European regional policy in the pre-treatment and post-treatment period. At the same time, we evaluate the presence of spatial spillover on provincial economic growth in response of regional European policy.

Figure 1 – Identification of Spatial Patterns by Local Moran's I



Source: Authors' elaboration

The total impact of the policy is disentangled in direct and indirect effects, i.e., in response to neighbours' state of treatment.

Table 3 resumes the findings of our analysis. The choice between spatial models is made on the basis of the Lagrange Multiplier tests for spatial dependence (Table 4). The results of the baseline model (1), a *DiD* model controlling for spatial clusters, show a positive and significant average treatment effect of regional policies implemented between 2007-2013 on the outcome measured by the 2015-17 gross domestic product growth rate. Note that the model captures the slowdown in the post-treatment period (negative coefficient of t) with a reduced resilience of the lagging regions (negative coefficient of *D*).

Table 3 – Direct and Indirect Effects on GDP Growth Rate

	Model 1: DiD	*Model 2: SDiD*	*Model 3: SDiD with Covariates*	*Model 4: SDM DiD*	*Model 5: SDEM DiD*
Constant	0.059***	0.064***	0.058***	0.050***	0.058***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
D	-0.011***	-0.009***	-0.015***	-0.015***	-0.016***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
t	-0.018***	-0.027***	-0.029***	-0.026***	-0.028***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)
Dt	0.029***	0.025***	0.021***	0.021***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
DjD		-0.020**	-0.022**	-0.023***	-0.020
		(0.009)	(0.009)	(0.009)	(0.014)
Djt		-0.013	-0.015	-0.019	-0.013
		(0.020)	(0.019)	(0.019)	(0.019)
DjDt		0.050**	0.048**	0.048**	0.043
		(0.025)	(0.024)	(0.024)	(0.028)
population growth rate			0.468***	0.455***	0.480***
			(0.062)	(0.062)	(0.063)
manufacturing employment growth rate			0.076***	0.077***	0.071***
			(0.012)	(0.012)	(0.012)
S10			0.003	0.003	0.001
			(0.003)	(0.003)	(0.003)
enlargement 2004 and 2007			0.033***	0.032***	0.035***
			(0.004)	(0.004)	(0.004)

(...continue...)

(...continue)

	Model 1: DiD	*Model 2: SDiD*	*Model 3: SDiD with Covariates*	*Model 4: SDM DiD*	*Model 5: SDEM DiD*
dummy capital			0.004	0.004	0.003
			(0.004)	(0.004)	(0.004)
dummy metropolitan area			0.005***	0.005***	0.005***
			(0.002)	(0.002)	(0.002)
Pre-treatment positive clusters	0.092***	0.093***	0.069***	0.069***	0.072***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Pre-treatment negative clusters	-0.057***	-0.056***	-0.050***	-0.049***	-0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
rho				0.155***	
				(0.06)	
lambda					0.42***
					(0.07)
Observations	2620	2620	2620	2620	2620
R^2	0.256	0.258	0.317		
Adjusted R^2	0.254	0.256	0.314		
Log Likelihood				4621.87	4635.73
$sigma^2$				0.002	0.002
Akaike Inf. Crit.				-9209.74	-9237.46
Residual Std. Error	0.043 (df = 2614)	0.043 (df = 2611)	0.042 (df = 2605)		
F Statistic	179.724*** (df = 5; 2614)	113.564*** (df = 8; 2611)	86.475*** (df=14;2605)		
Wald Test (df = 1)				6.663***	37.414***
LR Test (df = 1)				5.364**	33.085***

Source: Authors' elaboration.

Table 4 – Testing Spatial Dependence

Lagrange Multiplier diagnostics	*Statistic*	*Parameter*	*P-value*
LM spatial error	50.65	1	1.1e-12***
LM spatial lag	4.38	1	0.0364*
Robust LM spatial error	61.33	1	4.9e-15***
Robust LM spatial lag	15.06	1	0.0001***

Source: Authors' elaboration.

Model estimates are affected by the spatial dependence of outcome and treatment variables. We consider indirect effects produced by neighbouring regions that may have economic relations with the treated territories. Moreover, European regions are characterized by strong heterogeneity in growth rates, especially within EU15 regions and the newly annexed regions, admitted in 2004 and 2007.

In model 2 we present estimates of spatial DiD model using OLS estimator. The effect is equal to 0.025 while the covariate on spatial clusters shows higher coefficients. In fact, more significant variation is registered regarding the spatial clusters of hot-spots (0.093) and cold-spots (-0.056). This is not surprising, since the hot-spots (brown in fig. 1) represent the lagging regions, where higher growth is expected, and the cold-spots (purple in fig. 1) the more developed regions. Model 3 considers other covariates and, inter alia, a specific dummy for the regions belonging to newly annexed countries (*enlargement*). We find positive effects for the abovementioned regions, suggesting the driving force of cohesion policies leaning toward the convergence process. Considering spatial dependence in the outcome variable and between units, models 4 and 5 confirm our hypothesis of the existence of spatial effects, both direct and indirect. The average treatment effect is positive and equals 0.021, and it represents the direct impact of the policy, i.e., the difference on growth rates between treated and controls.

The indirect treatment effect (ITE) due to the presence of neighbours treated units is captured by the parameter Djt, that is negative and not significant. The indirect treatment effect on the treated (ITET) is measured by considering the interaction between own state of treatment and the one of neighbours, DjDt: the parameter is positive and significant in all the models.

The results suggest that regions cluster on territorial strengths. The spatial lag (rho) indicates that regions are expected to have higher GDP growth rates (Marica *et al*., 2021) if their neighbours have, on average, high GDP growth rates.

Finally, we provide the identification of different impacts in the preferred SDM DiD model (Table 5). Result confirms the presence of significant ITET

Table 5 – Marginal Effects of the SDM Estimates

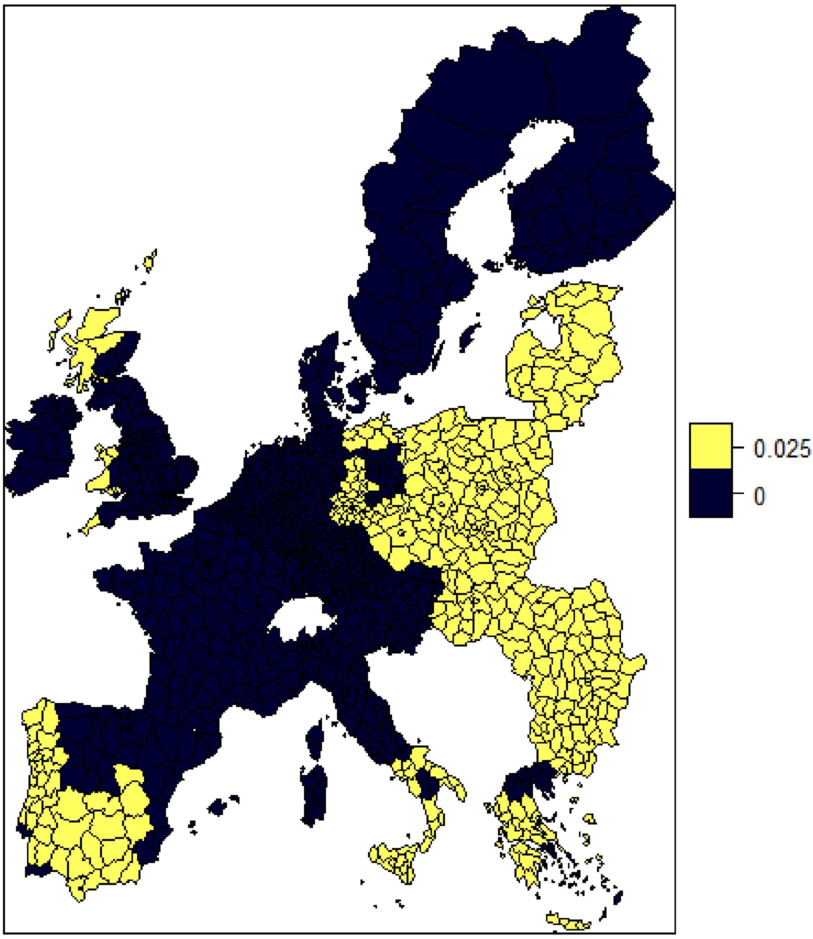
	Direct	*Indirect*	*Total*
D	-0.015***	-0.003*	-0.017***
	(0.004)	(0.001)	(0.004)
t	-0.021***	-0.005**	-0.031***
	(0.004)	(0.002)	(0.005)
Dt	0.021***	0.004**	0.025***
	(0.004)	(0.002)	(0.005)
DjD	-0.023***	-0.004	-0.028**
	(0.009)	(0.003)	(0.011)
Djt	-0.019	-0.003	-0.022
	(0.019)	(0.004)	(0.023)
DjDt	0.048**	0.009	0.057**
	(0.024)	(0.006)	(0.029)
population growth rate	0.455***	0.083**	0.538***
	(0.062)	(0.040)	(0.079)
manufacturing employment growth rate	0.077***	0.014**	0.091***
	(0.012)	(0.007)	(0.016)
S10	0.003	0.001	0.003
	(0.003)	(0.001)	(0.003)
enlargement 2004 and 2007	0.032***	0.006**	0.038***
	(0.004)	(0.003)	(0.005)
dummy capital	0.004	0.001	0.005
	(0.004)	(0.001)	(0.005)
dummy metropolitan area	0.005***	0.001*	0.006***
	(0.002)	(0.001)	(0.002)
Pre-treatment positive clusters	0.070***	0.013**	0.082***
	(0.005)	(0.006)	(0.008)
Pre-treatment negative clusters	-0.049***	-0.009**	-0.058***
	(0.005)	(0.004)	(0.005)

Source: Authors' elaboration

even when considered the presence of feedback effects (column indirect). In addition, the total average treatment effect is still positive and significant.

From the models we have decomposed the total effect of the policy in direct and indirect effects, following the approach presented in LeSage and Pace (2009) and

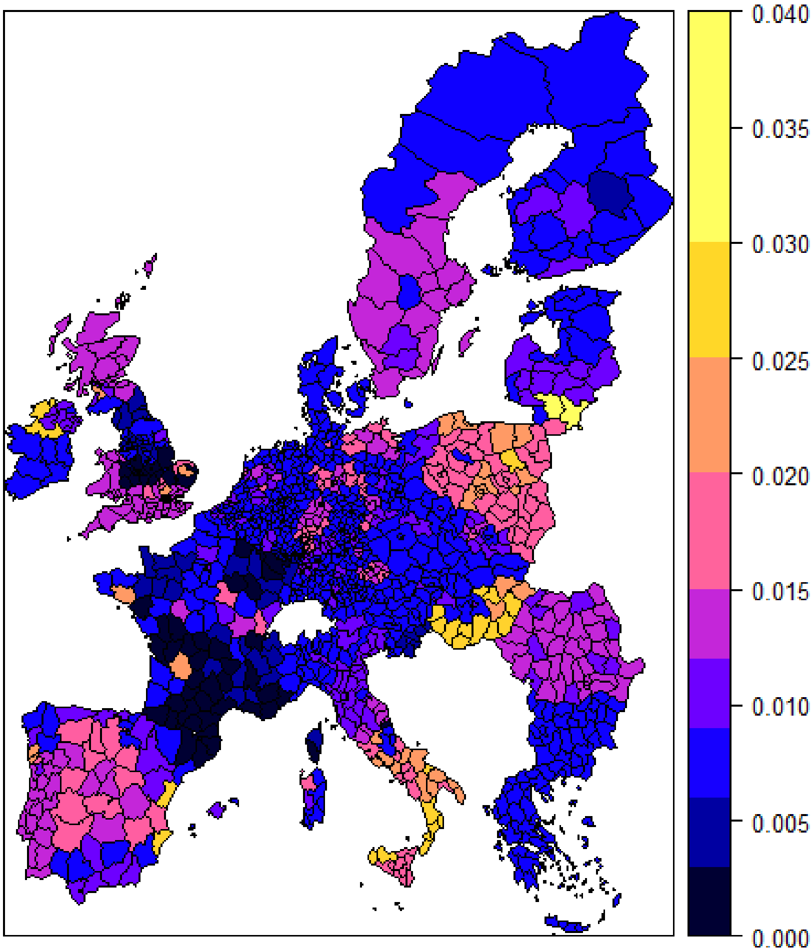
Figure 2 – Direct Effects of the 2007-2013 Cohesion Policy



Source: Authors' elaboration

Arbia *et al*. (2020). Overall, the indirect effects have the same sign as the direct effects, so they boost the output effect of the policy. In other words, Cohesion Policy of the programming cycle 2007-2013 succeeds in generating development processes in neighboring areas by strengthening the final effects expected by policy makers. By examining our preferred specification (the SDM model), Figure 2 shows how European regional policy is located in the weakest areas, where therefore its direct effects appear. More interesting is Figure 3, indicating the location and intensity of the indirect effects. These are generally grouped into geographic clusters. The most significant and largest cluster in terms of impact is represented

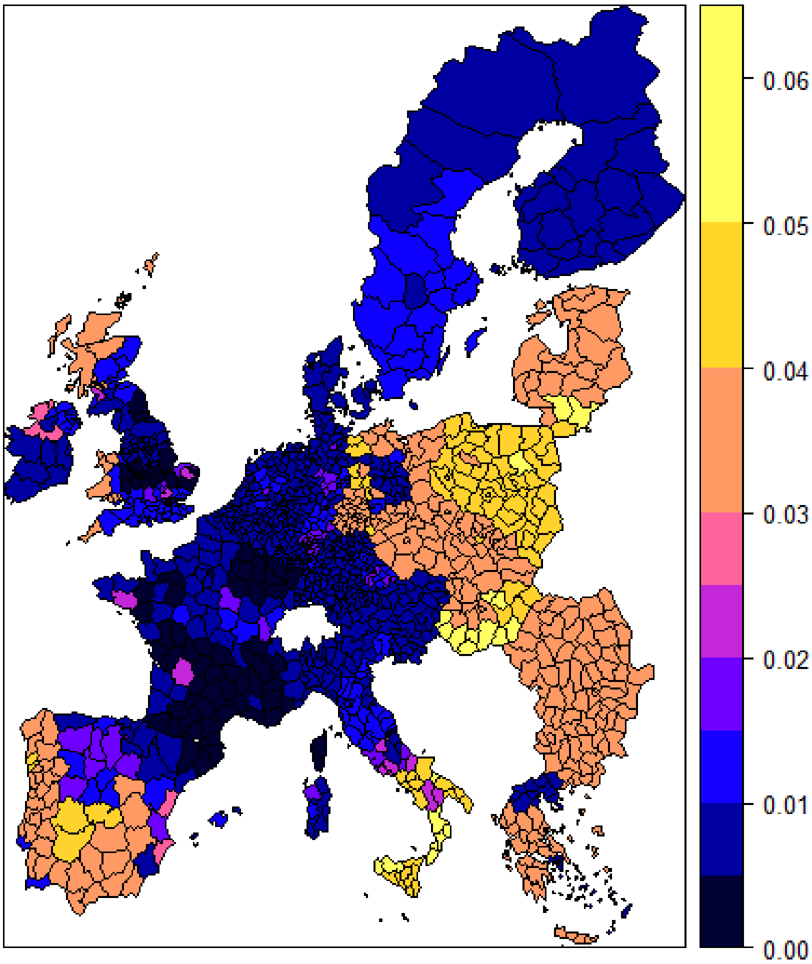
Figure 3 – Indirect Effects of the 2007-2013 Cohesion Policy



Source: Authors' elaboration.

by several regions in the Eastern Europe, including some new entrants. Also noteworthy is the cluster in the South Italy and in Ireland. The total effects, presented in Figure 4, are greater in the areas where the indirect ones are more relevant. Overall, the total effects are larger in areas of the European Eastern regions, where the policy produces high positive externalities, reducing inequalities with the more developed regions. In practice, this has strengthened resilience processes in these areas and thus reduced the gap with the more developed regions.

Figure 4 – Total Effects of the 2007-2013 Cohesion Policy



Source: Authors' elaboration

7. Conclusions

The aim of our work is to evaluate the total effects of European regional policy, considering both direct impacts and impacts due to spillovers. Unlike of the recent literature, our study considers the spatial configuration of regions in Europe and evaluate the effect to the clusters that have formed between developed and lagging regions.

This evaluation is based on a newly developed counterfactual approach, which at least partially overcomes the limits of the SUTVA, and consistently estimates the spillovers, which are detected based on the spatial distance between areas. The econometric model used is of the DiD type, with a spatial specification considering both the SDM and SDEM approach, clearly confirmed by the data.

The results confirm that the effects of regional policy on growth are positive also in the period considered (2015-2017). Therefore, also in a moment of economic downturn, European regional policy has helped the resilience of the weakest regions, which have been more exposed to the effects of the crisis.

The most innovative aspect of the analysis is the measurement of spillovers, which are positive, statistically significant, and therefore reinforce the impact of the policy. In the preferred SDM specification, about one-sixth of the overall policy effects are due to indirect effects attributable to the detected spatial spillovers. In the absence of an assessment of spillovers, the effects of the policy could not only be biased but also be underestimated.

The results underline how the structure of European regions empirically grouped into clusters, as shown by the analysis using Local Moran's I, interacts with spillovers. Empirically, these spillovers manifest themselves positively especially in the clusters of Eastern Europe, reinforcing the processes of convergence towards the more developed regions. This has therefore strengthened the resilience processes in these areas and contributed to an overall reduction of regional disparities in Europe.

The policy suggestions deriving from these results reaffirm the need to consider the total effects of the policies, including the spillover effects towards neighboring areas, in the evaluation of a place-based policy intervention. On the other hand, this is consistent with the place-based approach of the European policies which stimulate the processes of convergence of the European regions by enhancing the endowments of material, immaterial and human capital in the territory, also overcoming administrative boundaries. These results therefore suggest larger coordination of policies, overcoming administrative boundaries and having as an optimal dimension the geographical clusters of similar areas that are formed in the European space.

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Gli spillovers spaziali delle politiche regionali aiutano a ridurre le disuguaglianze regionali in Europa?

Sommario

La politica di coesione europea promuove lo sviluppo armonioso dell'Unione e delle sue regioni, favorendo la crescita inclusiva e l'occupazione nelle regioni meno sviluppate, migliorando il benessere delle persone e riducendo le disparità regionali. Tuttavia, gli effetti della politica sono sia diretti, nelle regioni in cui la politica viene indirizzata, sia indiretti, attraverso la generazione di effetti di ricaduta nelle regioni vicine o economicamente collegate. La valutazione degli effetti complessivi di queste politiche è quindi complessa, in quanto occorre tenere conto di entrambi gli effetti, diretti e indiretti. Tuttavia,

gli spillover sono generalmente esclusi dal modello controfattuale classico, che non ammette effetti di interferenza tra le unità trattate e non trattate della politica (ipotesi denominata SUTVA – Stable Unit Treatment Value Assumption). Il presente lavoro mira a superare questa restrizione, implementando una metodologia pienamente coerente con l'approccio controfattuale, che non ammette questa ipotesi. In questo lavoro, viene proposto un modello DID spaziale, basato sulla specificazione Modello Spaziale Durbin (SDM) che consente effetti di spillover. Il saggio valuta gli effetti complessivi della politica regionale del periodo di programmazione 2007-2013. I risultati mostrano effetti positivi della politica regionale europea specialmente nelle regioni dell'Est Europa, dove la politica produce esternalità positive elevate, riducendo le disuguaglianze con le regioni più sviluppate.