Structural Change and Economic Dynamics 67 (2023) 167–181

Contents lists available at ScienceDirect

Structural Change and Economic Dynamics

journal homepage: www.elsevier.com/locate/strueco

Convergence clubs and spatial structural change in the European Union

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ARTICLE INFO

JEL classification:
O47
R10
R11

Keywords:
Regional disparities
Club convergence
Structural change
Spatial dependence
Europe

ABSTRACT

This article studies regional income convergence and its conditioning factors in 267 subnational regions of the European Union during the 2003–2016 period. Building on previous research that documents the formation of multiple convergence clubs in per-capita income, we study the role of structural change and spatial dependence as key conditioning factors of the club convergence process. Our results are threefold. First, we document that the spatial distribution of the convergence clubs shows a strong degree of spatial dependence. Second, when we study the evolution of structural change and spatial dependence, our results show that the share of manufacturing has been decreasing, while its degree of spatial dependence has been increasing over time. In contrast, the share of knowledge-intensive services has increased, while its degree of spatial dependence has decreased. Third, we evaluate the role of structural change and spatial dependence in the formation of convergence clubs using a spatial ordered-logit model. Our results show that when spatial dependence is omitted from the econometric specification, both manufacturing and knowledge-intensive services are not significant predictors of club convergence. Only when spatial dependence is added to the specification do most of the structural change variables become statistically significant. In addition, there are contrasting spatial effects between variables of structural change. The geographical spillover effects for manufacturing and routine services are statistically significant, while knowledge-intensive services do not exhibit such significant spillover effects. Overall, our results highlight the joint importance of structural change and spatial dependence in the formation of convergence clubs. Specifically, the notion of spatial structural change deserves further attention, as it appears to play a major role in the evolution of regional disparities in the European Union.

1. Introduction

The European Union (EU) has long considered economic, social and territorial cohesion as fundamental goals, with the commitment of EU institutions to promote greater convergence and reduce disparities between member states. Currently, academics and policymakers are deeply concerned with understanding the emerging trends since there is evidence that inequality among EU regions has risen again in recent years after the slow convergence that took place during the 1990s and the early 2000s.

In particular, recent studies point to a ‘Great inversion’ according to which certain regions, cities and localities have pulled ahead in terms of economic prosperity, while many others have been left behind (Hendrickson et al., 2018; Iammarino et al., 2019; Rosés and Wolf, 2021; Storper, 2018; Martin, 2021). Meanwhile, it is uncertain what the future will be for regions that are ‘stuck in the middle’. Thus, these cities and regions that are not part of the global urban network and benefit neither from income subsidies nor structural funds deserve special attention (Moretti, 2012; Chapman et al., 2012; Iammarino et al., 2019; Diemer et al., 2022).

On a supranational scale, the geographical distribution of wealth across European countries and regions exhibits a persistent polarization pattern between rich regions in the northwest and poor regions in the southeast. Interestingly, recent studies have shown how macroeconomic imbalances in the Eurozone are tied to a structural polarization in terms of sectoral composition. Specifically, the emergence of export-driven growth in core countries and debt-driven growth in the Eurozone periphery can be explained by differences in the adoption of technologies and firm performance (Celi et al., 2018, Gräbner et al., 2020).

However, whether structural asymmetries at the macroeconomic level tend to be accompanied by divergent patterns within national borders remains an open issue. In this view, the nature and dynamics of structural change should be considered central in the empirical analysis of regional growth and convergence in the European Union, in particular, after the great recession (e.g. Groot et al., 2011, Martin and Sunley,

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https://doi.org/10.1016/j.strueco.2023.07.009
Received 8 December 2022; Received in revised form 21 June 2023; Accepted 24 July 2023
Available online 2 August 2023
0954-349X/

2015, Crescenzi et al., 2016). Various studies have indeed investigated the sources of regional disparities and the role of structural change at different subnational scales: NUTS 2 (Muštra et al., 2020), NUTS 3 (Angulo et al., 2018, Giannakis and Bruggeman, 2020), functional areas (Faggian et al., 2018), among others.

Our general proposition is that differences in growth paths and productivity are strongly associated with economic geography and historical development, in line with the theoretical predictions of both the New Economic Geography (NEG), the Evolutionary Economic Geography (EEG) and their foundational development theories (Myrdal, 1957, Hirschman, 1958).

On this perspective, the article aims to shed new light on the role of structural change and spatial dependence and its implications for understanding regional convergence dynamics in the European Union. By adding a more explicit spatial perspective in our empirical study, we aim to contribute to the recent literature on club convergence in Europe in the context of the Phillips and Sul (2009)'s approach. Specifically, we first complement the club convergence framework of Phillips and Sul (2007) by identifying statistically significant spatial clusters. Then, we analyze the conditioning factors behind club formation in a spatially augmented ordered logit model. This methodological approach allows us to quantify the role of spatial spillovers in the process of structural change.

The article is organized as follows. Section 2 presents the conceptual framework we rely on in this work and the relevant empirical literature. It provides an overview of previous contributions on club convergence and the role of structural change in Europe. Section 3 describes our empirical strategy and data. Sections 4 and 5 present and discuss the results, respectively. Section 6 offers some concluding remarks.

2. Related literature

2.1. Theory and empirics of economic growth: From conditional to club convergence in Europe

Drawing on the exogenous growth theory, the first two notions of convergence empirically scrutinized in the literature were beta-convergence and sigma-convergence.[1] However, several studies argued that the hypothesis of absolute convergence is hardly observed (e.g. Baumol, 1986, Romer, 1990, Lucas, 1988) paving the way to the conditional convergence hypothesis. Following Barro and Sala-i Martin (1992), Mankiw et al. (1992) provided the first evidence that an augmented Solow model with human and physical capital was more consistent with the observed cross-country data.

In the meanwhile, the debate within the endogenous growth literature produced fundamental contributions to the theoretical and empirical approach to growth. From a theoretical perspective, soon after Romer (1986) and Lucas (1988) had opened the 'black' box of technology, the endogenous growth theory provided further contributions allowing to escape from the law of diminishing returns. A purposeful research and development (R&D) was considered the engine of growth in the first generation of endogenous growth model (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992) and in the Shumpeterian models. It is worth noting that, although endogenous growth models differ in many respects, they all put knowledge at the center of an everlasting growth process both in the first generation and in the Shumpeterian models (e.g. Aghion and Howitt, 1992, Howitt, 1999).[2]

On the empirical ground, starting from the 1990s, a growing interest in the study of distribution dynamics accompanied the well-established analysis of beta- and sigma-convergence. Quah (1993) demonstrate that beta-convergence suffered from Galton's classical fallacy of regression towards the mean. Several contributions claimed that countries might not converge to a unique long-run steady state but rather form multiple convergence clubs even if the countries have access to similar technologies (Azariadis and Drazen, 1990, Azariadis, 1996, and Galor, 1996).

This multiplicity of locally stable stationary states is called club convergence. Club convergence is a kind of conditional convergence that emphasizes the initial conditions; countries and regions will approach a unique long-run growth path only if their initial conditions are in the same "basin of attraction". These properties entail policy implications as countries and regions can design and implement specific interventions to close the gaps in initial conditions that are responsible for divergent growth paths. Consequently, both within neoclassical theories and evolutionary approaches, the authors proposed new directions to more explicitly account for cross-country heterogeneity in the growth process, based on the existence of multiple steady states/regions, and accordingly claimed the need to study the entire distribution dynamics of income to provide a more realistic understanding of convergence (Durlauf and Johnson, 1995; Baumol, 1986; Galor, 1996; Quah, 1996). Along these lines, empirical studies shed light on the dynamics of countries' inequalities, bringing the idea of poverty traps and multimodal distributions.

The European economy has long been considered an interesting laboratory to empirically test the validity of the three different hypotheses of growth and convergence (see, e.g., Galor, 1996). According to Barro and Sala-i Martin (1992)), the convergence process in European countries was similar to that in the United States with a steady-state annual growth rate of about 2 per cent.

Early empirical studies identify a process of slow beta-convergence among EU countries and regions (e.g., Fagerberg and Verspagen (1996), Fingleton (1999a), Cuadrado-Roura (2001), Cappelen et al. (2003), Baumont et al. (2003), Carrington (2003), Meliciani (2006), Bosker (2007), Del Bo et al. (2010)).[3] However, recent studies on convergence in Europe seem to provide contrasting evidence. Some empirical studies provide evidence of higher convergence rates across countries, especially after the EU eastward enlargement starting from 2004 (Próchniak and Witkowski, 2013; Campos et al., 2014; Goedemé and Collado, 2016; Zoega and Phelps, 2019). Hence, one can conclude that the advantages of being part of the Single Market and the associated access to structural funds have helped growth in the New Member States. However, after the financial and debt crisis, regional income differences have increased, leading to income divergence between regions and, to a lesser extent, between countries (Von Lyncker and Thoennessen, 2017; Cutrini, 2019).

To summarize, although EU income disparities fell considerably over the last decades, this trend has stopped and unresolved asymmetries remain, threatening the convergence process after the financial and debt crisis in Europe (Monfort et al., 2013; Borsi and Metiu, 2015; Bolea et al., 2018). It should be noted that most of the first generation of empirical studies in Europe did not consider explicitly the spatial dimension of convergence.

[1] From a theoretical perspective, the neoclassical exogenous growth theory prescribes absolute income convergence for countries with identical technologies (e.g., Solow, 1956, Koopmans, 1965). Accordingly, beta-convergence indicates a process by which all regions are converging to the same steady-state level (Barro et al., 1991 and Barro and Sala-i Martin, 1992). In sigma-convergence, a set of countries or regions are said to converge if the cross-section standard deviation of their income per capita is decreasing over time (Barro and Sala-i Martin, 2004).

[2] See Aghion and Howitt (2008) for a complete discussion of endogenous growth models.

[3] E.g., Meliciani (2006) found that between 1988 and 1996 European regions have been characterized by a slow process of income convergence between countries and by a lack of income convergence between regions.

2.2. Spatial approaches to convergence and empirical evidence for Europe

Since the late 1990s, regional growth and disparities in the European Union have been empirically analyzed mainly through spatial approaches to convergence (Fingleton, 1999b; López-Bazo et al., 1999; Le Gallo et al., 2003; Le Gallo and Dall'Erba, 2003; Baumont et al., 2003; Abreu et al., 2005; Fischer and Stirböck, 2006; Ertur et al., 2006; Meliciani, 2006; Ezcurra et al., 2007; Dall'Erba et al., 2008; Le Gallo and Dall'Erba, 2008; Chapman and Meliciani, 2018).

The early contributions based on the distribution dynamics approach provide the first evidence of spatial dependence in the growth process of EU regions (see, e.g., Magrini, 2004, Fiaschi and Lavezzi, 2007, Maza et al., 2012). More recently, several works scrutinized the formation of spatial clubs in Europe (Baumont et al., 2003; Ertur et al., 2006; Le Gallo et al., 2003; Del Bo et al., 2010; Fischer and LeSage, 2015; Fiaschi et al., 2018; Annoni et al., 2019).

Spatial dependence (or spatial autocorrelation) can be defined as the degree to which an economic variable observed in one spatial unit is correlated with the same variable observed in neighboring regions. In studies of growth and convergence, issues of spatial dependence arise when the growth rate in one region is influenced by nearby regional growth rates.

The enlargement of the European Union in 2004 to include Central and Eastern European countries inevitably revived the convergence debate, with studies focusing on the convergence between the CEE-8 and the old EU-15 member states, both at national level (e.g. Cieślik and Wciślik, 2020) and regional level (Ezcurra et al., 2007, Postoiu, 2015, Völlmecke et al., 2016, Chapman and Meliciani, 2018).

Even if the results are still inconclusive, there is evidence that joining the EU has fostered cross-country convergence despite growing regional disparities within countries that have arisen in recent years. It is worth noting that within post-socialist countries, high-performing regions enjoyed higher per capita growth rates because of the presence of a skilled labor force, relatively developed infrastructure, advanced services, human capital-related technological endowment, and a marked increase in foreign investment during the 1990s Ezcurra et al., 2007; Chapman and Meliciani, 2018; Völlmecke et al., 2016; Borsekova et al., 2021. Studies on spatial correlation contribute to the understanding of the new economic geography of Europe after the eastward enlargement. Ertur et al. (2006) found strong evidence of global and local spatial autocorrelation as well as spatial heterogeneity in the distribution of regional per capita GDP in a sample of 258 European regions including regions from acceding and candidate European countries over the period 1995–2000. Ertur et al. (2006) show that accession of Central and Eastern European countries disturbs the previous North–South polarization pattern of the EU. The geographical dynamics of EU15 was indeed dominated by an increasing clustering of population and wealth in a central area delimited by North Yorkshire (UK), Franche-Comté (France), and Hamburg (Germany), known as the core. In the enlargement context, this previous North/South polarization pattern is replaced by a new North–West/ East pattern in EU27. Similarly, Ezcurra et al. (2007) found a tendency towards geographical clustering of less developed regions. Spatial concentration levels are considerably lower in the more developed regions, however. These results are in line with Postoiu (2015) which found some spatial clustering of regions that lag behind, while high-performing regions are rather isolated.

In general, there is evidence that, despite the overall reduction in regional inequality between 1990 and 2001, and the convergence of income between all regions of the EU during the decade 2001–2010, regional disparities within CEEC countries have increased significantly in the last period analyzed (Ezcurra et al., 2007; Chapman and Meliciani, 2018; Völlmecke et al., 2016). The rise of disparities within CEEC countries was due to two tendencies. On the one hand, the strong dynamism of the large urban areas, the regions hosting the capital cities that act as attraction poles, and the regions close to the EU15 border. On the other side, the decline in old industrialized, rural, and peripheral lagging regions further contributes to increasing regional divergence within CEECs countries (Ezcurra et al., 2007; Meliciani, 2006; Chapman et al., 2012; Chapman and Meliciani, 2018; Völlmecke et al., 2016; Postoiu, 2015; Borsekova et al., 2021).

In a context of high and persistent regional disparities and differentiated spatial dependence, the club convergence hypothesis can be assumed as an appropriate theoretical device to interpret the widely agreed idea of a 'multi-speed' Europe. Moving from this perspective, empirical evidence on club convergence in the EU based on subnational spatial units, that is, NUTS 1–2 levels, has continuously developed and is gaining momentum after the Great Recession because of growing concerns on the current surge of inequalities among EU regions (Iammarino et al., 2019), among others).

Empirical studies confirmed that it is possible to identify at least two convergence clubs in Europe for periods spanning before the global financial crisis (Quah, 1996; Le Gallo and Dall'Erba, 2003; Le Gallo and Dall'Erba, 2006; Corrado et al., 2005; Mora et al., 2005; De Siano and D'Uva, 2006; Fischer and Stirböck, 2006; Battisti and De Vaio, 2008; Artelaris et al., 2010; Fischer and LeSage, 2015; Bartkowska and Riedl, 2012; Fiaschi et al., 2018). The geography of Europe emerged more fragmented from analyses that include a period after the Great Recession sufficiently long to capture the effects of the financial and debt crises (Von Lyncker and Thoennessen, 2017; Cutrini, 2019; Mazzola and Pizzuto, 2020).

Bartkowska and Riedl (2012) studies the role of high-tech production and services and found that the level of other initial conditions, such as human capital and per capita income, plays a crucial role in determining the formation of convergence clubs among European regions. They also included a first attempt to account for spatial spillovers by studying the role of neighboring regions' per capita incomes for a given region's club membership. Von Lyncker and Thoennessen (2017) found that industry and services' shares are significant determinants of club memberships, they also provide confirmation of a North-South divide.

Cutrini (2019) investigated the link between the evolution of spatial inequalities and structural change in Europe and found that polarization increased after 2008. Club convergence of regions depends on regional economic structures, with membership in high-income clubs predicted by the presence of an important manufacturing base and the specialization in high productivity services.

Despite this rich empirical literature, relatively few studies have attempted to more explicitly account for spatial heterogeneity and spatial dependence in a club convergence analysis of European regions (Baumont et al., 2003; Le Gallo and Dall'Erba, 2003; Le Gallo and Dall'Erba, 2006; Ertur et al., 2006; Fischer and Stirböck, 2006; Fischer and LeSage, 2015; Battisti and De Vaio, 2008; Bartkowska and Riedl, 2012; Annoni et al., 2019). Moreover, to what extent and how structural change and spatial dependence interact has remained a substantially overlooked topic in the related literature.

2.3. Industrial agglomeration, knowledge spillovers, and structural change. The 'borrowed size/agglomeration shadow' framework

This article starts with the premise that structural change and the associated location of industries and services over space matter for club convergence. The conceptual approach adopted here is rooted in the intersection of different strands of the literature - economic geography, urban economics, and innovation literature - that widely acknowledged the importance of spatial interactions and urban agglomeration economies.

As for the theoretical underpinnings of agglomeration and spatial spillovers, both New Economic Geography and evolutionary theories provide insights into possible mechanisms that can explain the tendency of growing disparities, leading to divergence. Divergence can derive from knowledge spillovers and other agglomeration forces, particularly in urban areas. After the seminar contribution of Krugman

(1991), where agglomeration is the result of interaction between demand, scale economies and transport costs, it is worth mentioning the alternative models of Krugman and Venables (1995) and Venables (1996) allowing production within each industry to contain several intermediate stages, each of which is characterized by increasing returns to scale. Cost and demand linkages due to the intermediate usage of goods are at the origin of manufacturing agglomeration. Under certain conditions, complementarities between the location decisions of upstream and downstream firms cause all firms to agglomerate in one region. Industry agglomeration is, in this case, the result of localized firms that share backward and forward linkages (Hirschman, 1958).

Beyond the intra-sectoral linkages that are the classic source of localization economies, it is also important the role played by urbanization economies. In regional science and urban economics, localized knowledge spillovers, labor market considerations, and the provision of public goods are the critical determinants behind urban agglomeration externalities. According to Duranton and Puga (2003), agglomeration economies characterizing the cities relate to three micro-founded mechanisms, i.e., sharing, matching, and learning[4].

The micro-foundations of urban agglomeration economies refer to greater availability of services, better infrastructure endowment, knowledge diffusion, the presence of public goods, and a more dense and varied labor market that favors the best match between the demand and supply of labor. Hence, denser functional areas facilitate the connection between the qualifications required by employers and the characteristics of employees.

Overall, the first empirical evidence for Europe was generally in line with the hypothesis of clustering of knowledge-intensive services (KIS) in dense urban areas. Skilled labor and human capital tend to concentrate in regions with large urban areas, further accelerating the functional specialization of cities in knowledge-intensive and high-skilled activities (Jacobs, 1969; Duranton and Puga, 2005). According to Duranton and Puga (2005), production in Europe has, on aggregate, been moving from locations where headquarters and R&D functions tended to be clustered (the cities) towards peripheral locations.

Nevertheless, a complementary view within the EEG claims that interactions for KIS are not necessarily defined by geographical proximity and sectoral proximity might be more important (Boschma, 2005).

Following the same line of reasoning, Meliciani and Savona (2015) pointed out the crucial role of inter-sectoral linkages between manufacturing and business services to understand the recent specialization patterns and innovation potentials of European regions. In particular, they highlighted that inter-sectoral interdependencies (e.g., between high-skilled services and knowledge-intensive industries) and the need to share tacit knowledge could interfere with the agglomeration forces acting towards the spatial concentration of KIS in large cities[5].

Further conceptual frameworks in the urban economics domain provide additional insights that are relevant to our study. Polèse and Shearmur (2006) claimed that the spatial distribution of economic activities exhibits regularities with respect to city size and distance, in a Christaller logic. In this respect, important concepts for the present analysis are the notions of the 'borrowed size' effect and the opposite 'agglomeration shadow' effect. The former was first coined by Alonso (1973) and then used in Phelps et al. (2001), Phelps (2004) and, more recently, by Meijers et al. (2016), Meijers and Burger (2017) for the European context. The latter, the so-called 'agglomeration shadow' effect, was first introduced by Krugman (1993) within the NEG literature.

It is useful to bring together the concepts of borrower size and agglomeration shadow (Meijers and Burger, 2017). On one side, the borrowed size effect refers to the process of suburban growth interlinkages -cities which are integrated into polycentric urban forms- and is the result of the tension between agglomeration and dispersion forces (Phelps, 2004). On the other hand, growth near concentrations of firms will be limited by competition effects. Hence, positioning within the 'shadow' could not be profitable for firms (Meijers and Burger, 2017).

Moving from the same framework,[6] Burger et al. (2015), Cardoso and Meijers (2016) provided evidence for Europe that the distribution of high-end cultural amenities in North-West Europe still follows a Christallerian logic, with a concentration of consumer services in larger cities such as Vienna, Berlin, and Paris (Burger et al., 2015). At the same time, the places that lie in the shadow of these central places are confined to lower levels of high-end cultural amenities than could be expected given their size. In other words, on average, larger cities in Europe cast a shadow over smaller neighboring cities rather than these smaller cities borrowing size from their larger neighbor. It is easy to highlight the parallelism between the borrowing size/agglomeration shadow framework and the tension between Myrdal (1957)'s spread and backwash effects (Volgmann and Rusche, 2020). Borrowed size effect fosters economic and population growth in nearby regions (spread effect) while agglomeration shadow produce a 'displacing effect' (backwash effect) with service- based activities moving away form the hinterland to concentrate in urban centres, in line with the empirical evidence provided by Meliciani and Savona (2015) and Polèse and Shearmur (2006).

Hence, going beyond the so-called 'footloose hypothesis' (Wernerheim and Sharpe, 2003)[7], it is possible to claim that region-specific factors may also affect the location of knowledge-intensive activities leading to the possibility of concentration of business services not only in large urban areas, but also in specific regions, where customers in high-tech manufacturing sectors are located or where ICTs and public R&D facilitate the development of an innovative local environment (Meliciani and Savona, 2015). On this perspective, the spatial

[4] Based on club theory, the first mechanism deals with sharing indivisible facilities, with two main advantages for firms and consumers. First, a large final-goods industry allows for sustaining a wider variety of input suppliers; second, large production allows to rip the gains from narrower specialization. According to the Smithian argument, higher specialization can increase productivity for three reasons: first, learning by doing; second, the stability of workers' tasks allows for saving on fixed costs (such as training, for example); third, the division of labor fosters labor-saving innovation because the mechanization of simple tasks becomes easier. As for matching and risk sharing, they represent important mechanisms to fulfill labor pooling, and a justification of the advantage of large cities in reducing the risk of being unemployed. The basic idea, to use Alfred Marshall's words, is that "a localized industry gains a great advantage from the fact that it offers a constant market for skill". Irrespective of the different typologies, a trade-off exists between urban agglomeration economies and urban crowding. The second mechanism relies on the matching externality typical of cities. As the number of agents increases, trying to match improves, either on the supply or on the demand side, the chances and the expected quality of each match. The third mechanism is related to learning (Duranton and Puga, 2003).

[5] Location choices in business services depend on the nature and the services' innovative content. When it is necessary to share tacit knowledge, like in the case of KIS, spatial contiguity does matter. In this case, business services firms can find it convenient to follow manufacturing firms even if they locate far from the major cities (Meliciani and Savona, 2015).

[6] The argument works as follows: (1) First-tier cities or capital cities are the ones with a higher share of KIS and with higher employment growth in most innovative activities and knowledge-intensive services; (2) Functional specialization of higher order regions in knowledge-intensive functions such as KIS lead to competition effects that outweigh the borrowed size effect (Burger et al., 2015). The neighboring regions lie in the shadow of first-rank city regions (usually capital regions) and face spatial competition effects for a variety of services, especially knowledge-intensive and creative activities.

[7] Wernerheim and Sharpe (2003) suggest that some services do not need to be located in urban centres because they can be supplied entirely online without the need for geographical proximity.

concentration of BS has been viewed as the result of the increasing volume and complexity of knowledge and the need to manage it through spatial proximity (Ciarli et al., 2012; Meliciani and Savona, 2015).

Interestingly, Meliciani and Savona (2015) also claim that while the location of valued-added and knowledge-intensive activities in large metropolitan areas may foster city development[8], it could also cause negative externalities in surrounding areas.

Their arguments are generally supported by empirical evidence on the spatial concentration of BS in European capital regions. Their analysis suggests that, while being surrounded by highly populated regions results into positive spillovers, being surrounded by regions with capital cities exerts a negative indirect effect on specialization in BS. It appears that in the case of capital cities there is a strong 'displacing' effect with services-based activities moving away from surrounding areas to concentrate in urban centres. Similarly, Polèse and Shearmur (2006) found that the most dynamic service industries are centrality-seeking and have important implications for the evolution of income disparities at the regional level.

3. Methods and data

3.1. Convergence test and club identification

In this article, we employ the econometric approach proposed by Phillips and Sul (2007) to test the hypothesis that all subnational regions of the European Union will eventually converge to a single long-term equilibrium. This approach is particularly relevant given the ongoing discussion on regional integration in Europe and whether all member states will eventually achieve similar economic performance. Phillips and Sul (2007) based their log-t convergence test on a non-linear time-varying factor model. The model begins with the decomposition of panel data for GDP per capita (X_{it}) into two components:

$$X_{it} = g_{it} + a_{it}, \tag{1}$$

where g_{it} is a systematic component and a_{it} is a transitory component. To distinguish between common and idiosyncratic components, Eq. (1) can be rewritten as:

$$X_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t, \tag{2}$$

where μ_t and δ_{it} indicate the common component and the idiosyncratic component, respectively. δ_{it} indicates the distance between the common component μ_t and X_{it}. Due to the impossibility of directly estimating the loading coefficients, δ_{it}, without imposing a structure on δ_{it} and μ_t, the common component can be eliminated by constructing the following relative transition paths:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N}\delta_{it}}. \tag{3}$$

Together, Eq. (4) and Eq. (3) point out the two main properties of the transition paths h_{it}. First, the cross-sectional average of h_{it} is equal to one. Second, the relative transition parameter h_{it} converges to one if the factor loading coefficients δ_{it} converge to δ_i. Asymptotically ($t \to \infty$), the cross-sectional variance of the relative transition parameter, H_t, approaches zero in this case ($H_t \to 0$). Then, we can use this second property to test the null hypothesis of regional convergence. Specifically, regional convergence occurs when

$$H_t = N^{-1}\sum_{i=1}^{N}\left(h_{it} - 1\right)^2 \to 0 \text{ as } t \to \infty. \tag{4}$$

In this modeling context, Phillips and Sul (2007) propose the following log-t regression model to test the regional convergence hypothesis:

$$\begin{aligned} &\log\left(H_1/H_t\right) - 2\log(\log(t)) = a + b\log(t) + u_t \\ &\text{for } t = [rT], [rT]+1, \dots, T \text{ with } r > 0, \end{aligned} \tag{5}$$

where H_t is the cross-sectional variance of relative GDP per capita at time t, and H_1 is the same measure in the initial year. The left-hand side of the equation is the difference between the logarithm of these two measures, adjusted for the logarithm of the time interval between them. The right-hand side of the equation is a linear function of the logarithm of time, with a constant term a and a slope coefficient b. The term $[rT]$ indicates the initial observation in the regression, which implies that the first fraction of the data is discarded.

The Phillips and Sul (2007) convergence framework uses Eq. (5) to test for convergence among different economies. If the slope coefficient b is negative and statistically significant, it suggests that the economies are not converging over time. For statistical inference purposes, Phillips and Sul (2007) recommend using a one-sided t-test with heteroskedasticity and autocorrelation-consistent (HAC) standard errors. In this setting, if the t-statistic is less than −1.65, the null hypothesis of regional convergence is rejected at the 95% level of significance.

In addition to the convergence test, Phillips and Sul (2009) propose a clustering procedure to identify convergence clubs if the convergence hypothesis is rejected throughout the sample. This clustering process consists of the following five steps:

1. Cross-sectional ordering: Sort the regions in decreasing order on the basis of their last observation.

2. Formation of the core group: Select the first k highest regions to form the subgroup G_k for some $2 \le k < N$. Next, apply the log-t regression (Eq. (5)) to obtain the convergence test statistic for this subgroup. Then choose the size of the core group k^* by maximizing the t-statistic over the convergence criterion $t_b > -1.65$. If $t_k > -1.65$ does not apply to $k = 2$, remove the highest region of the core group and repeat the algorithm for the rest of the sample.

3. Sieving regions for club membership: The remaining regions are added one by one to the core group (G_k) and the log-t test is repeated. If the t-statistic is greater than −1.65, a new group is formed.

4. Recursion and stop: Group all regions that could not be selected in Step 3. Apply the log-t test to this subgroup. If $t_k > -1.65$, this indicates that there are two convergence subgroups. Otherwise, steps 1 through 3 are repeated. If no core group is found, the remaining regions are labeled divergent, and the algorithm stops.

5. Club merging: Perform the log-t test for all pairs of initial clubs. If the convergence criterium is satisfied, the clubs should be merged. Repeat this procedure for the remaining clubs until the convergence criterion is rejected.

3.2. Determinants of club membership

In the second step, we analyze the characteristics of the different clusters identified according to relevant initial conditions and variables capturing the sectoral composition, paying attention to consider separately different categories of services, because of their diverse skill intensity. We estimate ordered logit regressions with club membership as the dependent variable and compute the predicted probability. The predicted probability is the implied probability that a given region belongs to a certain convergence club. To evaluate the relevance of our variables of interest in determining club membership, we compute the marginal effects of the predicted probabilities. They show the change

[8] They suggest that centripetal and centrifugal forces can explain the location of BS in larger urban areas. Three forces are mentioned: - The classical sources of localization and urbanization externalities; – The role of intermediate demand and, in particular, the structure of intermediate linkages between BS and their manufacturing users and the region-specific sectoral structure; – The region-specific innovation and knowledge infrastructure, particularly the ICT intensity.

in probability when the predictor increases by one unit, while all other explanatory variables are set at their sample average.

When examining the determinants of club membership, a growing body of research has evaluated the importance of spatial spillovers from neighboring regions (Bartkowska and Riedl, 2012; Li et al., 2018; Ursavas and Mendez, 2022). Motivated by this literature, we first identify each region's geographical neighbors based on a six-nearest-neighbors criterion. Next, we compute the mean neighbor performance for the economic structure variables: manufacturing share, knowledge-intensive services share, and routine services share. In the literature of spatial econometrics, these neighborhood averages are known as spatial lags, and they are used are proxies for the performance of each region's geographical neighbors. In the context of the ordered logit model, we interpret the effect of these spatial lags as indicators of a "spatial structural change" process.

3.3. Spatial dependence methods

On the basis of the geographic distribution of a variable, we first apply an analysis of global spatial dependence. This analysis helps to evaluate the hypothesis of spatial randomness and the presence of a general spatial clustering pattern. The Moran's I indicator is the most common statistic used to evaluate this hypothesis (Anselin, 1995; Anselin et al., 2007). In the analysis of the regional income distribution, the Moran's I statistic describes the relationship between one location's income values and those of nearby locations. If Moran's I differs statistically from 1/(N-1), where N is the number of regions, then the hypothesis of spatial randomness is rejected. In most cases, the numerical values of Moran's I range between −1 and +1. When its value is close to one (minus one), spatial autocorrelation is positive (negative). Positive spatial autocorrelation represents spatial similarity and an overall clustering pattern, whereas negative spatial autocorrelation represents spatial dissimilarity and a checkerboard pattern.

Next, to identify the specific location of the spatial clusters and outliers, we apply an analysis of local spatial dependence (Anselin, 1995; Anselin et al., 2007). In terms of measurement, this analysis is typically based on the decomposition of a global statistic of spatial dependence. In particular, a local analysis of spatial dependence allows us to divide the regions into four groups. The first two groups describe spatial cluster locations. The first type of spatial clusters consists of high-income regions surrounded by other high-income regions (that is, a high-high cluster). The second type of cluster depicts low-income regions surrounded by low-income regions (that is, a low-low cluster). The third and fourth groups describe the location of spatial outliers. The first type of spatial outlier represents regions with high-income values surrounded by low-income regions (that is, a high-low group). The second type of outliers consists of low-income regions surrounded by high-income regions (that is, a low-high group).

Finally, we apply a spatial ordered logit model to study the role of spatial spillovers in the formation of convergence clubs. For that purpose, we first identify the six nearest neighbors of each region.[9] Second, we compute the mean values of the manufacturing and service shares based on these neighbors. In the literature on spatial econometrics, these mean values are known as spatial lags and represent the performance of each region's geographical neighbors. Third, we include these spatially lagged variables in an ordered logit model as in Bartkowska and Riedl (2012) and Ursavas and Mendez (2022).

In the context of the spatial econometrics literature, our econometric specification is commonly referred to as an SLX model. The main features of this model are that spatial dependence only occurs in the explanatory (X) variables and that spillovers effects are local in nature. Compared to other spatial models, Elhorst and Vega (2015) and Elhorst (2018) argue that the SLX model has some useful features for applied research. First, the SLX model is parsimonious in nature. It enables estimation using conventional econometric estimators, including non-linear ones such as those employed in the ordered logit and probit models. Second, spillover effects are directly captured through the coefficients of the spatially lagged (X) variables. This is not the case for other more complicated models, such as the SAR, SAC, or SDM, where the spatial dependence occurs in the dependent (Y) variable. Third, the SLX model offers flexibility in measuring spillover effects, in contrast to models like SAR and SAC, which require a constant spillover ratio across all variables.[10]

3.4. Data

The analysis is based on a panel database of regional data from 2003 to 2016. Our research concentrates on the 2003–2016 period, enabling us to establish a basis for comparing our findings with the most related previous literature. Specifically, we adopt the identical sample period employed by Cutrini (2019) to investigate the consequences of introducing additional variables into the model, particularly the implications of EU membership and spatial dependence on club convergence.

Regional data is collected from several sources contained in Eurostat, the official statistical office of the European Union. GDP per capita is measured in purchasing power standards (PPS). Population growth is measured as average growth over the analysis period (2003–2016, source Regional demographic statistics, Eurostat); private investment is proxied by gross fixed capital formation as a share of population (source: Regional branch accounts (ESA 2010), Eurostat). Human capital is measured as the share of the population aged 25–64 with upper secondary, post-secondary non-tertiary and tertiary education, corresponding to levels 3–8 of the International Standard Classification of Education (ISCED) (Source: Regional education statistics (ISCED 2011), Eurostat).[11]

To account for the potential role of urbanization economies we employ the database compiled by the Joint Research Centre and the European Commission Directorate General for Regional Policy. Agglomeration effects are based on data on urban-rural typology of NUTS3 regions according to three typologies – predominantly urban, predominantly rural, intermediate – and other local information. We focus on the location of metropolitan areas and we classify our spatial units of analysis according to the numbers of metropolitan areas (NUTS3 metro-region) included in each NUTS2 region. We then re-scale our indicator

[9] We also use the six nearest neighbors for the analysis of global and local spatial dependence. To evaluate the robustness of the spatial regression to the number of nearest neighbors, in Appendix C we use two additional weights matrices with four and eight nearest neighbors, respectively. Overall, the results are largely robust, with the exception of the spatial marginal effects of the manufacturing share.

[10] Although the spatial Durbin model (SDM) is a commonly used specification in modern spatial econometrics research, its application to ordered logit or probit models – with multiple categories – is less predominant. Lacombe and LeSage (2018) provide an illustrative application of a SDM framework for a probit regression. However, similar to SAR probit model of LeSage et al. (2011), this application is only available for two non-ordered categories. Aware of this methodological limitation, we use a SLX framework that easily accommodates the five ordered categories of the dependent variable.

[11] To facilitate comparability of results with Cutrini (2019) we opted for the same basic explanatory variables. Moreover, we believe that this enlarged operational definition of human capital is better suited to capture matching processes, based on labor market micro-foundations highlighted in Section 2.3 (Duranton and Puga, 2003). We are aware that such an extended version of human capital is not a good proxy for the highly skilled workforce available, in terms of formal educational attainment. However, other skills (e.g., in manual tasks or organizational skills) are equally important to explain the different regional trajectories of development, especially when all the regions of enlarged Europe are considered, as in our case. These kinds of human capital are hardly measured with the available data on educational attainment because they require learning by doing processes.

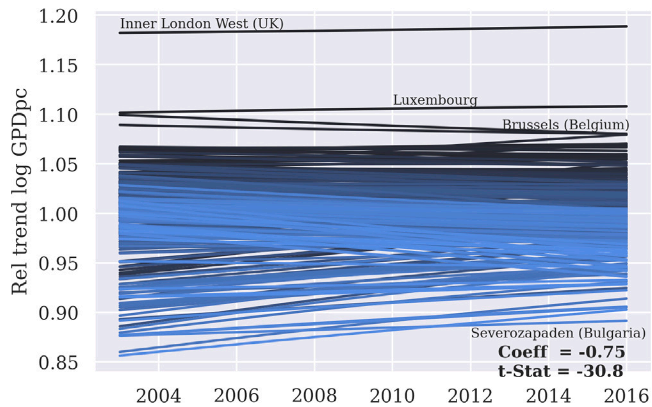

Fig. 1. Evolution of GDP per capita and convergence test.
Notes: The null hypothesis of convergence is rejected when the t-statistic is less than −1.65. Appendix D provides an alternative scatter-plot visualization of these regional mobility patterns.

which provides a synthetic picture of the degree of urbanization so that it varies from 0 to 1.

During recent years European countries have continuously shifted from production-based economies to economic systems dominated by the service sectors, especially in urban areas. Hence, for the remaining variables that capture the economic structure, this study not only distinguishes between manufacturing and service sectors but also allows to identify the contribution to economic growth of different kind of services, namely, high-wages services and low-wages services. We thus differentiate, within the tertiary sector, between Knowledge-intensive business services (KIBS), and Routine services. Knowledge-intensive services industries are composed by a set of sectors that, according to the NACE Rev 2 classification, are Information and communication (J), Professional, scientific and technical activities, and Administrative and support service activities (M-N). Routine services include Wholesale and retail trade (G), Transport and storage (H), and Accommodation and food service activities (I). Structural variables are included in our empirical analysis as the share of employment in the respective sector over the total number of employed persons in all NACE activities (NACE Rev 2).

4. Results

4.1. Convergence clubs and spatial clusters

In this section, we present the dynamics of (log) GDP per capita in terms of their club convergence classification and spatial distribution. Fig. 1 shows the relative long-run trends of the logarithm of GDP per capita.[12] For each region in each year, the logarithm of GDP per capita is normalized by the cross-sectional mean. As a result, the average for each year is equal to one. This data re-scaling is not only a requirement for the convergence test, but also facilitates the interpretation of trends in the data. For instance, Inner London West shows a large income level difference when compared to other regions. In 2003, its (log) GDP per capita was 18 percent above the average of the sample, and by 2016 it remained at that relative level.

In the context of the long-run trends of Fig. 1, we now evaluate whether all regions convergence to a common long-run equilibrium. Although the dynamics of relatively low-GDP regions may visually indicate a reduction in GDP gaps, results from the log-t test of Phillips and Sul (2007) reject the hypothesis of regional convergence. As the convergence coefficient is −0.75 and the t-statistic is −30.8, we conclude that the regions are not converging to a common long-run equilibrium. As a next step, we need to evaluate the possibility of local club convergence.

[12] As in Phillips and Sul (2009), long-run trends are estimated using the Hodrick–Prescott filter with a smoothing parameter of 400.

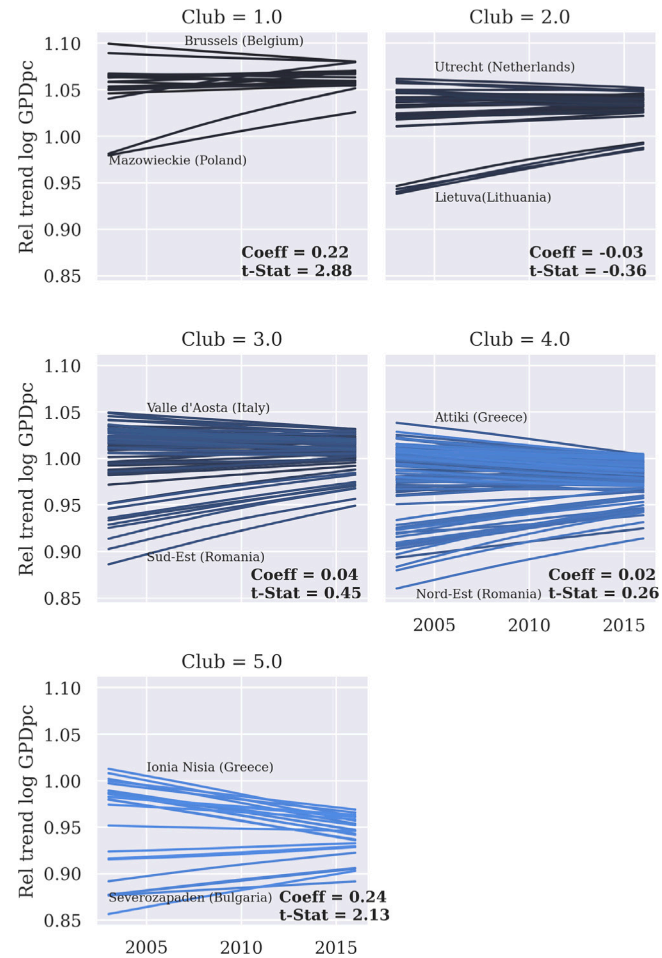

Fig. 2. Convergence clubs.
Notes: The null hypothesis of convergence is rejected when the t-statistic is less than −1.65. Inner London–West and Luxembourg are diverging regions.

Based on the clustering algorithm of Phillips and Sul (2009), Fig. 2 shows that the per-capita GDP dynamics of Europe are characterized by five convergence clubs. For all these clubs, the t-statistic is greater than −1.65, thus the null hypothesis of convergence is not rejected within each club. However, three caveats are worth noting. First, not all regions are allocated to a club. London-West and Luxembourg are classified as divergent regions. Second, Club 2 is a "weak" club in the sense that its convergence coefficient is negative, but its t-statistic is greater than −1.65. Third, at the end of the sample period, there is a considerable overlap between Club 3 and Club 4.[13] Despite these caveats, this convergence-club classification of regional economies is highly consistent with that reported in the previous literature (Cutrini, 2019).[14]

[13] The overlap in club membership indicates that certain regions had similar income levels in the last year of the sample period. However, these regions belong to different clubs due to significant differences in their long-term trends, which were calculated over the entire sample period.

[14] The null hypothesis of convergence is rejected even after removing Inner London West and Luxembourg from the analysis. See Appendix E for further details.

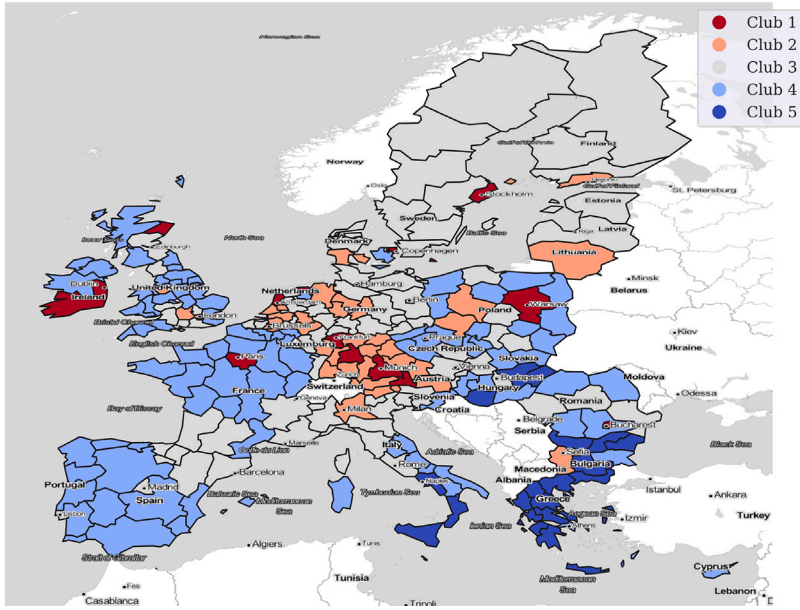

Fig. 3. Spatial distribution of the convergence clubs. Notes: For further visual details, an interactive online version of the map is available when clickingHERE.

Fig. 3 shows the spatial distribution of the convergence clubs. The most noticeable feature of this distribution is the geographical clustering of the convergence clubs. Low (high)-GDP regions tend to be surrounded by other low (high)-GDP regions that belong to the same club. However, geographical clustering is much weaker for Club 1, which is largely composed of capital cities. Despite the geographical sparsity of Club 1, the overall location of the convergence clubs points out a core–periphery structure that characterizes the geographical distribution of per-capita GDP in Europe.

Fig. 4 provides an analysis of the local spatial dependence in the distribution of relative (log) GDP per capita.[15] Panel (a) shows one of the most commonly used frameworks to study spatial dependence: the Moran scatter plot. On the horizontal axis, we measure the relative (log) GDP per capita and indicate the regional mean with a vertical line. On the vertical axis, we measure the relative (log) of GDP per capita of the six nearest neighbors of each region and indicate the mean with a horizontal line. Regional units can be located in one of four possible quadrants: high-high (HH), low-low (LL), low-high (LH), and high-low (HL). The slope of the regression line indicates the strength of spatial dependence. The results of panel (a) show a considerable degree of positive spatial dependence: High (low)-GDP regions tend to be surrounded by high (low)-GDP regions. Based on a conditional permutation approach (Anselin, 1995), we can identify statistically significant regions that are located mainly in the HH and LL quadrants. When plotting these regions on a map (see panel b), we confirm that very high-income regions with positive spatial dependence are in a central area of the so-called "Old Europe" while the low-low regions are mostly located in South East Europe. Therefore, the analysis of the spatial dependence of GDP per capita is consistent with the spatial structure reported in Fig. 3.

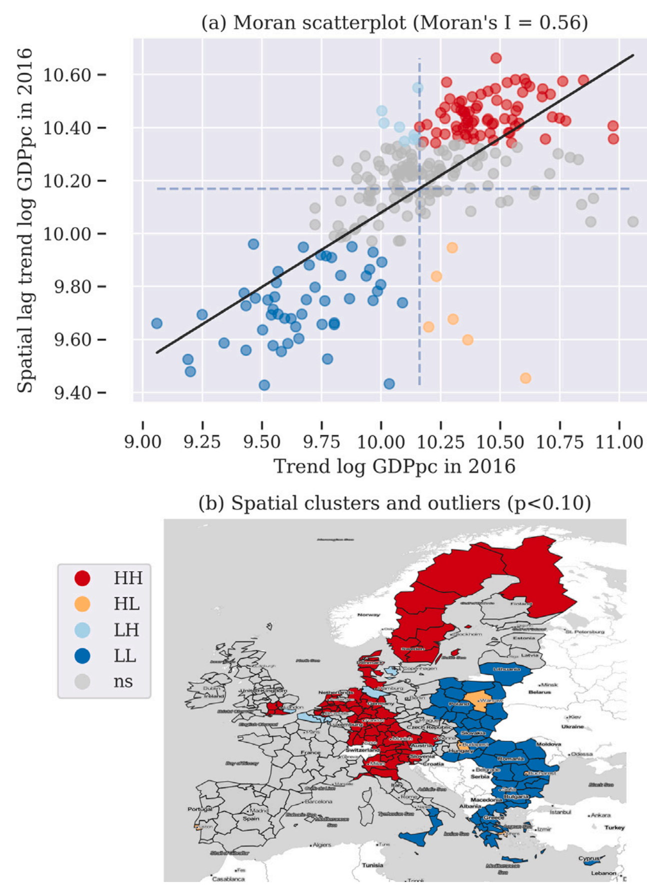

Fig. 4. Spatial dependence of the trend of log GDP per capita in 2016. Notes: HH and LL indicate spatial clusters while HL and LH indicate spatial outliers.

4.2. Economic structure and spatial dependence

Fig. 5 shows the evolution of structural change and spatial dependence over the 2003–2015 period. Panel (a) points out how the employment share of manufacturing, knowledge-intensive services, and

[15] To increase comparability, both Figs. 3 and 4 utilize the same measure: the long-term trend of GDP per capita (in logarithmic terms), calculated yearly using the Hodrick–Prescott filter. However, it is worth noting some limitations in their comparison. Fig. 3's clusters arise from analyzing the entire time series from 2003 to 2016, while Fig. 4's clusters are determined based on the spatial relationships observed in 2016. Due to these methodological differences, Ursavas and Mendez (2022) argue that these clustering results could serve as complements, not substitutes. Fig. 3 overlooks the spatial interdependencies among regions, whereas Fig. 4 neglects the temporal dynamics.

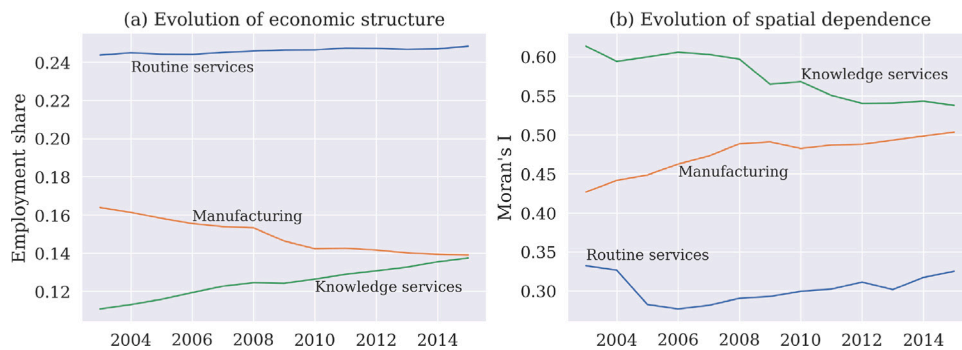

Fig. 5. Evolution of economic structure and spatial dependence.

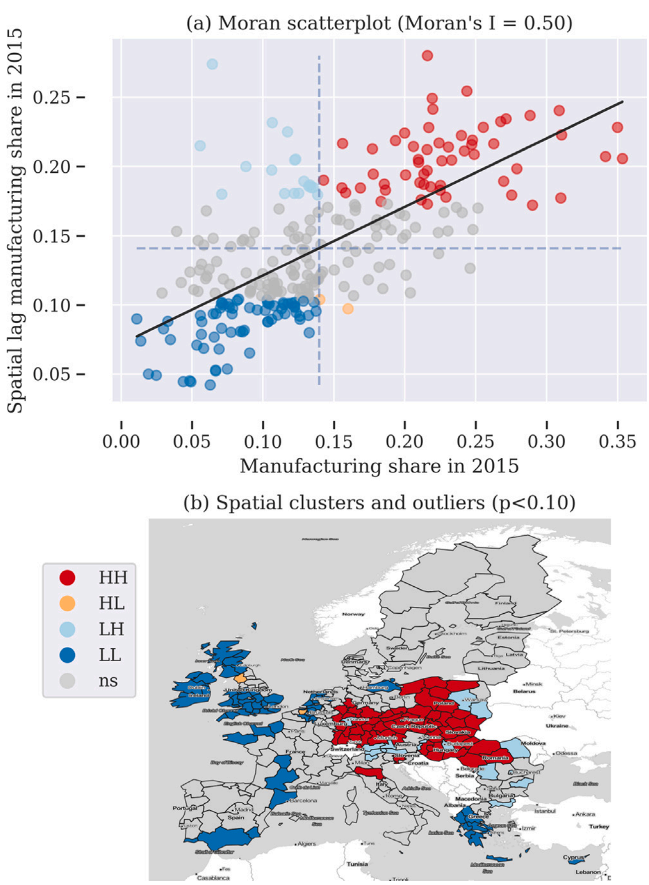

Fig. 6. Spatial dependence in manufacturing share in 2015.

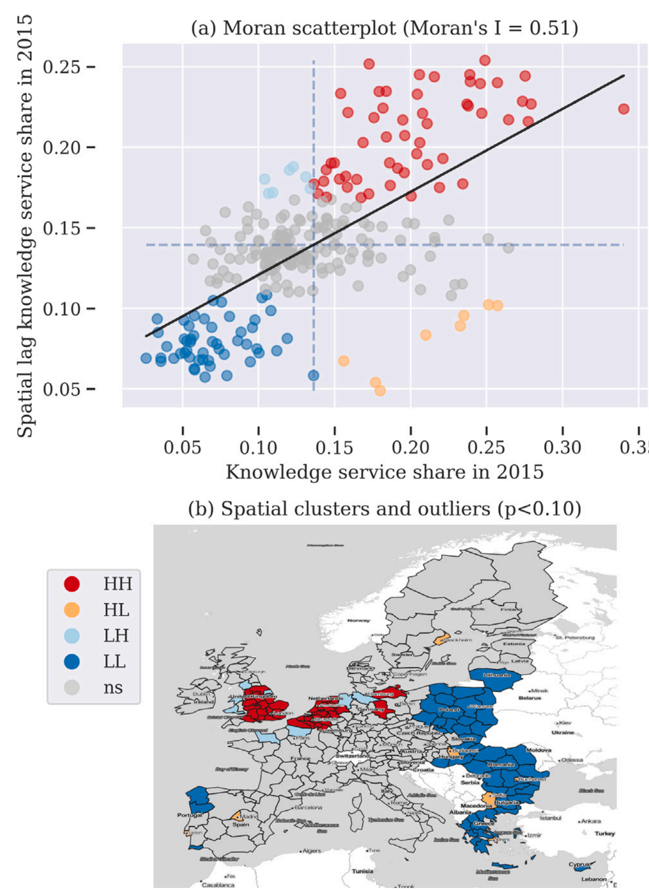

Fig. 7. Spatial dependence in knowledge-intensive services share: 2015.

routine services have changed over time. The share of manufacturing employment has been decreasing, while the share of services has been increasing. When focusing on the latter, knowledge-intensive services show a fast rate of change, while level of routine services remains the highest.

Panel (b) points out how spatial dependence in the employment shares has changed over time. Similar to panel (a) of Fig. 4, we compute the Moran's I, but this time we consider its dynamics over the entire 2003–2015 period. The spatial dependence in manufacturing has been systematically increasing, while the spatial dependence in knowledge-intensive services has been decreasing. Despite this reduction, the level of spatial dependence in knowledge-intensive services remains the highest in the three sectors considered. Spatial dependence in routine services has initially reduced, but it has been increasing since 2005.

Figs. 6 to 8 show a more detailed view of the spatial patterns of manufacturing, knowledge-intensive services, and routine services. Similarly to Fig. 4, we identify spatial clusters and outliers based on the four quadrants of the Moran scatterplot. Compared to the spatial clusters of GDP per capita, a core–periphery structure in employment shares appears less evident. Only for knowledge-intensive services (Fig. 7), we find some similar spatial clusters in the southeast of Europe. The regions located in this spatial cluster not only show a low share of knowledge-intensive services, but also show the lowest levels of GDP per capita (Fig. 3).

In particular, Panel (b) of Fig. 7 illustrates the three main topics of this article: convergence clubs, economic structure, and spatial dependence. Regions located in the southeast part of Europe share three characteristics. First, they are converging to relatively low-income clubs (see Club 4 and Club 5 in Fig. 3). Second, they show a low share of employment in knowledge-intensive services (Fig. 7) Third, they show a high degree of spatial dependence in both income (Fig. 4) and economic

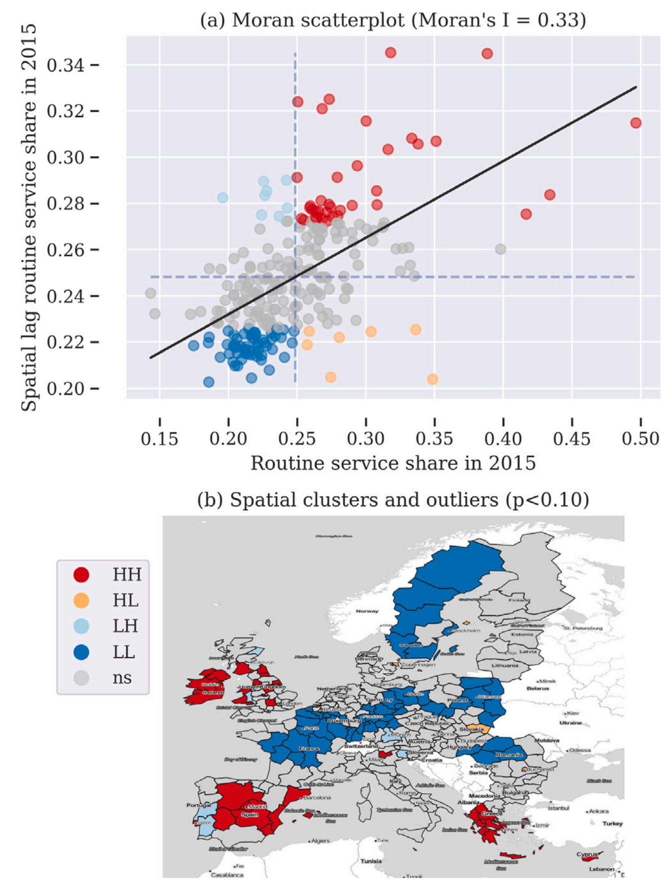

Fig. 8. Spatial dependence in routine services share: 2015.

structure (Fig. 7). Motivated by this example, in the next section, we study convergence clubs, economic structure, and spatial dependence in a more unified framework.

4.3. Club determinants and spatial structural change

Table 1 shows the results of the non-spatial benchmark model. The variables are organized into tree blocks: structural change, growth fundamentals, and other control variables. Among the structural change variables, only the share of employment in routine services is statistically significant. Furthermore, the direction of the marginal effects for each club is consistent with the results of Cutrini (2019) in the sense that regions with large shares of routine services are more likely to join low-income clubs. Among the fundamentals of economic growth, only the education variable is statistically significant. The direction of the marginal effects is intuitive, as the regions with a largely educated population are more likely to join high-income clubs. Among other control variables, both the initial level of GDP per capita and the new EU membership indicator are statistically significant. Consistent with previous studies, the initial level of income is a highly significant predictor of club membership (Bartkowska and Riedl, 2012; Von Lyncker and Thoennessen, 2017; Cutrini, 2019). In addition, we find that joining the EU decreases the probability of joining low-income clubs and increases the probability of joining high-income clubs.

Although the results of Table 1 point to some specific factors that condition club membership, they do not account for the role of spatial interactions between regions. By construction, the ordered logit model of Table 1 assumes that the performance of a region is independent of that of its geographical neighbors. However, this assumption can be highly restrictive in the context of structural change. For instance, it is difficult to image the manufacturing performance of the Spanish regions as independent of that in the Portuguese regions. The extensive literature on economic geography and global value chains highlights the role of interactions across multiple geographic units or economies. In this context, Table 2 aims to account for the role of spatial interactions in variables related to structural change.

Table 2 shows the results of a simple spatial logit model. Variables are organized into four blocks: non-spatial structural change, spatial structural change, growth fundamentals, and other control variables. In this model, spatial structural change is conceptualized based on spatially lagged variables. Intuitively, spatial lags represent the average performance of the neighbors of each region. Adding these variables not only improves the overall fit of the model, but also recovers the statistical significance in manufacturing and knowledge-intensive services.

The main results of Table 2 highlight the spatial channels of structural change.[16] Unlike Table 1, manufacturing is a significant predictor of club convergence in Table 2. Specifically, an increase in the spatial lag of manufacturing increases the probability of joining high-income clubs. In other words, when the geographical neighbors of a region increase their share of manufacturing, the region increases its probability of joining high-income clubs. The opposite pattern characterizes the share of routine services. That is, when the geographical neighbors of a region increase their share of routine services, the region decreases its probability of joining high-income clubs.

Table 2 also indicates that the share of knowledge-intensive services is a significant predictor of club convergence, but in a different way compared to manufacturing or routine services. The spatial lag of knowledge-intensive services is not statistically significant. This result suggests that geographical spillover effects tend to be more present in manufacturing and routine services. On the contrary, the lack of significant geographical spillovers in knowledge services may indicate that knowledge interactions are not necessarily defined by geographical proximity (Boschma, 2005). For example, many financial and consulting services can occur entirely online without the need for geographical proximity. However, manufacturing and routine services are largely dependent on transportation costs, which vary with geographical distances. As such, the gains of location similarity in knowledge services may not be as large as the location gains associated with manufacturing and routine services.

5. Discussion

In this section, we provide an interpretation of our results in light of the literature surveyed in Section 2.

First, our results point to a clear geographical clustering of lagging-behind regions in southeast Europe which is also characterized by a similar spatial clustering in terms of economic structure. A low share of knowledge-intensive services is associated with the lowest level of GDP per capita (cf. Figs. 7, 3, and 4). Furthermore, we find that very high income regions are either clustered in a central European manufacturing core area, or more isolated, with a highly scattered spatial distribution corresponding to capital regions or first-tier regions of each EU country. These results are in line with previous evidence, in particular, those of Ezcurra et al. (2007), Postoiu (2015), and Chapman et al. (2012)).

Second, our econometric analysis (Table 2) suggests that knowledge-intensive services are a significant determinant of high-income club membership. In addition, we confirm the role of more

[16] Given our fixed sample, the inclusion of spatial lags in the model limits the degrees of freedom for our estimates. This inclusion could be especially costly on the marginal probabilities of Club 1 (n=20) and Club 5 (n=22), both of which have a smaller member count. A more comprehensive study focused on NUTS3 regions could provide a solution to this limitation.

Table 1
Determinants of club membership: Base model with no spatial dependence.

Variables	(1) Club 1	(2) Club 2	(3) Club 3	(4) Club 4	(5) Club 5
Structural change					
Manufacturing share	0.03	0.19	0.31	−0.50	−0.03
	(0.04)	(0.31)	(0.51)	(0.80)	(0.05)
Knowledge intensive services share	0.05	0.39	0.62	−1.00	−0.06
	(0.07)	(0.44)	(0.75)	(1.16)	(0.08)
Routine services share	−0.19***	−1.34***	−2.15***	3.45***	0.22**
	(0.07)	(0.38)	(0.69)	(0.91)	(0.09)
Growth fundamentals					
Ln gross fixed capital formation	−0.00	−0.01	−0.01	0.02	0.00
	(0.00)	(0.02)	(0.03)	(0.05)	(0.00)
Ln population with high education	0.02**	0.16***	0.25***	−0.41***	−0.03**
	(0.01)	(0.05)	(0.10)	(0.14)	(0.01)
Other control variables					
Ln GDP per capita	0.09***	0.67***	1.08***	−1.74***	−0.11***
	(0.03)	(0.16)	(0.24)	(0.30)	(0.04)
Urbanization degree	0.01	0.07	0.11*	−0.18*	−0.01
	(0.01)	(0.05)	(0.07)	(0.11)	(0.01)
New EU member	0.06**	0.40***	0.64***	−1.02***	−0.07***
	(0.02)	(0.13)	(0.16)	(0.25)	(0.02)

Standard errors in parentheses. All predictors at their mean value.
*p<0.1
**p<0.05
***p<0.01

Table 2
Determinants of club membership: Model with spatial dependence in structural change variables.

Variables	(1) Club 1	(2) Club 2	(3) Club 3	(4) Club 4	(5) Club 5
Structural change					
Manufacturing share	0.00	0.05	0.10	−0.14	−0.01
	(0.03)	(0.37)	(0.77)	(1.13)	(0.04)
Knowledge intensive services share	0.11*	1.25**	2.58**	−3.80**	−0.15
	(0.06)	(0.57)	(1.15)	(1.59)	(0.09)
Routine services share	−0.01	−0.14	−0.28	0.41	0.02
	(0.03)	(0.37)	(0.77)	(1.14)	(0.05)
Spatial structural change					
W*Manufacturing share	0.09	0.94	1.95*	−2.87*	−0.11
	(0.06)	(0.61)	(1.16)	(1.70)	(0.08)
W*Knowledge intensive services share	−0.05	−0.54	−1.12	1.65	0.06
	(0.05)	(0.54)	(1.09)	(1.59)	(0.07)
W*Routine services share	−0.22**	−2.40***	−4.97***	7.31***	0.29**
	(0.10)	(0.75)	(1.52)	(1.95)	(0.14)
Growth fundamentals					
Ln gross fixed capital formation	−0.00	−0.01	−0.02	0.02	0.00
	(0.00)	(0.02)	(0.04)	(0.05)	(0.00)
Ln population with high education	0.01*	0.15**	0.31*	−0.45*	−0.02
	(0.01)	(0.07)	(0.18)	(0.24)	(0.01)
Other control variables					
Ln GDP per capita	0.05***	0.58***	1.20***	−1.77***	−0.07**
	(0.02)	(0.13)	(0.26)	(0.27)	(0.03)
Urbanization degree	0.00	0.03	0.06	−0.09	−0.00
	(0.00)	(0.04)	(0.08)	(0.12)	(0.01)
New EU member	0.02**	0.27***	0.56***	−0.83***	−0.03**
	(0.01)	(0.10)	(0.18)	(0.24)	(0.01)

Standard errors in parentheses. All predictors at their mean value.
*p<0.1
**p<0.05
***p<0.01

traditional determinants already emerged as significant drivers in previous comparable contributions, namely, a high initial GDP per capita and a medium-high level of educational attainment (Bartkowska and Riedl, 2012; Von Lyncker and Thoennessen, 2017; Cutrini, 2019).

These two key results confirm prior work documenting the pivotal role of capital regions hosting business services. In line with the urbanization literature, many of the regions highly specialized in BS are regions where capital cities are located (Jacobs, 1969; Glaeser et al., 1992; Glaeser, 1999). This applies not only to high-income European countries, but also to Spain, Portugal, and Greece and to some new member states such as Hungary and Czech Republic (Ciarli et al., 2012 and Meliciani and Savona, 2015).

Third, our estimates suggest that the EU membership favors the convergence of a region towards high-income clubs. In this respect, our paper confirms prior work documenting the pro-growth effect of EU enlargement for those countries of Central Eastern Europe that joined the EU from 2004 onward (Ertur et al., 2006 and Zoega and Phelps (2019), among others), despite CEECs regions without capital cities are significantly lagging behind the rest of Europe (Borsekova et al., 2021). Hence, regional disparities within some of the New Member States may have increased due to a 'urban bias' in growth (Eckert et al., 2020), i.e. a comparative advantage of cities in skilled services, whose evidence for capital regions will be discussed in more detail below.

Fourth, in terms of spatial structural change, we argue that spread-backwash processes should be envisaged as non-dichotomous[17] as already pointed out by Gaile (1980) and in the tension between borrowing size and agglomeration shadow effects. In the present analysis, we find that 'trickling down' effects dominate in manufacturing activities while services exert "backwash effects' in nearby regions leading to differential spatial development patterns.

The possible explanations behind the different spatial spillovers observed in manufacturing and in service activities[18] are worth further scrutinizing.

First, the economic geography of local production systems in Europe has changed considerably since 2000 as has the way these are linked to the global economy. The positive and significant spatially lagged manufacturing shares of our spatial logit model (Table 2) suggest that spatial spillovers have been important in reshaping industrial employment in an enlarged Europe. We suggest that positive spatial dependence of neighboring regions for manufacturing stems from the growth of new clusters in CEEs countries that have emerged in those older industrial regions bordering the EU to reduce transport cost of raw materials and intermediate inputs, as in the NEG arguments surveyed in Section 2.2.

The reshaping of EU-wide value chains has resulted in the co-location of establishments in relatively close geographical proximity, thus contributing to the agglomeration of industrial employment in the so-called 'Central European Manufacturing core' (Stehrer and Stöllinger, 2015) as it is clear from Fig. 6 that shows how in 2015 the High-High spatial cluster for manufacturing corresponds to a central area delimited by Germany and Austria and extending eastward towards some of the most dynamic regions of Poland, Czech Republic, Slovakia, and Hungary. Hence, the accession of Central and Eastern European countries has disturbed the previous North–South polarization pattern of the EU, as suggested by Ertur et al. (2006).

As it is well known, the spatial reorganization of industries has occurred through the unboundling of manufacturing value chains and their extension from the Older Member States towards New Member States in Central and Eastern Europe (CEE) that have joined the European Union since 2003 onward. Qualitative evidence with several case studies highlighted how the border regions of CEE benefited from their recent accession to the EU, in terms of industrialization and growing employment (OECD, 2013). Likewise, the EU agglomeration of manufacturing activities in a well-defined area is also evident under our analysis of global and local spatial dependence. Studying the evolution of the Moran's I indicator over the 2003–2015 period we found a systematically increasing global spatial dependence (Fig. 5). Furthermore, the H-H spatial cluster is characterized by the co-location of regions with high manufacturing shares and geographically overlaps the 'Central European Manufacturing Core' (Fig. 6).

Instead, we argue that slightly predominant backwash effects across NUTS-2 regions may explain the opposing evolution in services. The Moran's I indicator is low for routine services throughout the period and the degree of spatial dependence of knowledge-intensive services has been continuously declining (Fig. 5, panel (b)). We suggest that expansion in capital regions or metropolitan regions has backwash effects in nearby localities, due to a preexisting comparative advantage of cities in non-tradable services and skilled services.

In our analysis, KIS regional specialization is positively and significantly correlated with the respective region's growth. Instead, we find that the coefficient associated with the spatially lagged variable is negative for both categories of business services we included in our analysis, although not significant for KIS.

We interpret our results on spatial interactions related to services considering the tension between the borrowing size effect and the agglomeration shadow, a framework developed in the regional and urban economics domain and surveyed in Section 2. In this perspective, we suggest that our results based on the NUTS2 grid point to a backwash effect which outweighs the borrower size effect. If the latter had prevailed, the growth of economic activities in the neighboring regions would have occurred. Consequently, in our estimates, the coefficient of the lagged variable would have been positive. Instead, our results of spatial competition effects are in line with the evidence provided by Polèse and Shearmur (2006), Meliciani and Savona (2015) and Meijers and Burger (2017).

Moreover, we argue that selective migration is a major channel through which such a cumulative process unfolded in Europe in recent years, in line with fundamental contributions in the development theory (Myrdal, 1957). In this respect, our results further support the hypothesis of 'displacing effects' are at work and complement empirical evidence documenting spatial competition effects for innovative and knowledge-intensive activities in lower-income regions (Annoni et al., 2019, Cutrini, 2023).[19]

In line with the argument put forward by Annoni et al. (2019), we may suggest that neighboring regions with more sophisticated business environments attract physical and human capital, producing a negative effect on growth in one's own region and thus may further worsen short-distance inequalities in the lagging-behind areas of Europe. This hypothesis is further corroborated by our analysis based on the LISA cluster approach applied to the GDP per capita in 2016. We found that significant spatial outliers with a High-Low patterns are located in Central and South-East Europe and correspond to capital regions, namely Warsaw, Budapest, Bucharest and Athens (Fig. 4).

Further support for the hypothesis of 'agglomeration shadow' partially counter-balanced by 'borrowing size' effect comes from a visual

[17] This is a different view than the one introduced in the original, nearly simultaneous contributions of Myrdal (1957) and Hirschman (1958). Myrdal's 'backwash effects' are conceptually analogous to Hirschman's polarization effects exerted by urban areas to nearby regions. Similarly, Myrdal's spread effects are equivalent to Hirschman's 'trickling down' effects.

[18] In the spatial ordered logit model, we found positive and significant spatial effects in manufacturing and negative spatial spillovers effects in services. Yet, these are significant only for routine services (Table 2). It is worth noting that, in our analysis, most of the sectors classified as routine services are non-tradable local consumer services that tend to cluster where the population density and economic activities are higher, such as the major cities.

[19] Annoni et al. (2019) use business sophistication as a proxy for innovative activities. They found, in the peripheral regime, a negative and weak spillover effect in their spatial Durbin model regression. Likewise, Cutrini (2023) find that the spatial lags of KIS shares are negative and robustly significant in the low-income club.

inspection of the map depicting the location of P&S clubs. Panel (a) of Fig. 3 highlights that many of the regions belonging to Club 1 are national capitals or first-tier cities, especially within North and Central Europe. Club 2 involves many cities and national capitals elsewhere in the EU. Relevant to our hypothesis of spatial competition is that capital regions (most of them located in the higher-income Clubs 1 and 2) tend to be surrounded by lower-income clubs, as evidenced by Fig. 3. In the latter regions, second-tier or small and medium-sized cities are usually located (Clubs 4 and 5).

In this respect, London is a case in point, as a global city with a highly dynamic environment shaped by its unique agglomeration of financial services, creative and knowledge-intensive activities. Other first-tier cities in several European countries share the same pattern, even though to a lesser extent (ESPON, 2013; Clark et al., 2019). Several other examples in North-West Europe and Central Europe evoke a possible 'displacing' effect exerted by the capital regions to nearby areas. Both Dublin and Paris belong to Club 1 while their neighboring regions belong to Club 4. Berlin, Vienna, and Bratislava are capital regions belonging to Club 1 but surrounded by regions that are part of Clubs 3 and 4. Warsaw belongs to Club 1 with neighboring regions classified by the P&S algorithm as Club 4. Some further examples can be found in South-East Europe: Madrid and Lisbon, each of them belonging to Club 3 but surrounded by regions belonging to Club 5. Rome and Budapest are both in Club 3 while their neighboring regions belong to Clubs 4 and 5. Sophia (Club 2) is surrounded by regions belonging to Club 5; Bucharest belongs to Club 1, while its neighboring regions belong to Clubs 4 and 5.

It is worth noting that our results sound consistent with the evidence provided by Polèse and Shearmur (2006) and Meliciani and Savona (2015). Polèse and Shearmur (2006) found that the most dynamic services industries are centrally-seeking, and Meliciani and Savona (2015) also found that being surrounded by regions with capital cities exerts a negative indirect effect on specialization in business services (their dependent variable).

6. Concluding remarks

This article analyzes club convergence in Europe adopting a more explicit spatial perspective than usually done in previous studies. We first complement previous convergence results of Cutrini (2019) with an analysis of global and local spatial dependence to identify the location of significant spatial clusters. Next, we study the role of spatial spillovers in the formation of convergence clubs through the inclusion of spatially lagged variables related to structural characteristics of regions in an ordered logit model, in the same vein as in Bartkowska and Riedl (2012) and Ursavas and Mendez (2022). Our club convergence analysis identifies five clubs across NUTS 2 regions. We detect a significant degree of spatial dependence in the employment share of manufacturing and services. These results suggest that spatial dependence plays a role in the formation of clubs. The results of the spatial ordered logit models indicate that initial per capita income, human capital, EU membership, and knowledge services are important drivers of club membership.

Taken together, our results suggest that the EU core–periphery spatial pattern has tended to fade away after the eastward enlargement and the global financial crisis. The previous North/South polarization pattern is replaced by a more complex new North – West/South – East pattern in the EU27, with capital regions and main cities acting as stable attractors of jobs, highly educated workers, and wealth. The complementary between club convergence and spatial dependence analyzes provide a more detailed picture of the geography of economic activities and regional convergence. This complementarity helps us understand the factors behind the dynamics of high-performing regions, those that are stuck in the middle, and those that are lagging behind.

In particular, we found that regional specialization in knowledge-intensive services fosters regional growth, but it could also cause negative externalities in surrounding areas, i.e., the agglomeration shadow effect partly outweighs the borrowing size effect.

Alternatively, it is also possible that the extent of knowledge spillovers is geographically self-contained within the NUTS-2 regions, and positive externalities could emerge only with analyses based on the NUTS-3 partition grid. Moreover, a further limitation of our study is that we could not consider the distinction between low-tech and high-tech manufacturing industries, due to data availability. Accordingly, we suggest two main directions for future research. First, it is important to explore whether our results can be confirmed at a higher spatial granularity. Second, it should be important to assess the spatial dependence of knowledge-intensive activities – also within the manufacturing sectors – to gauge the extent of inter-sectoral linkages more thoughtfully.

Finally, we acknowledge that more research attention should be paid to intermediate regions (those belonging to Clubs 2, 3, and 4), as they may have different capacities and regional resilience (Dijkstra et al., 2015). Some of these regions are at high risk of falling into a development trap, regardless of their income level (Diemer et al., 2022). Looking ahead, these regions deserve special attention from European and national decision-makers. Therefore, we suggest that further analysis might explore the process of spatial structural change along two lines. First, what will be the future of the regions that are 'stuck in the middle'? Analyses focused on these intermediate clubs could reveal a more detailed scenario that is useful to define targeted policy interventions. Furthermore, we suggest that future research should focus on more recent dynamics during and after the COVID-19 pandemic. Not only because the pandemic may have altered the spatial organization of manufacturing and services, but also because the attempts of policymakers to rebuild the economy through the Next Generation EU program may produce relevant effects on regional inequalities within the EU.

CRediT authorship contribution statement

Eleonora Cutrini: Conceptualization, Methodology, Data curation, Writing, Visualization, Reviewing and editing. **Carlos Mendez:** Conceptualization, Methodology, Data curation, Writing, Validation, Visualization, Software, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This article was presented at the 63rd Congress of the Italian Economic Association in Turin (October 20–22, 2022) and the 61st ERSA Congress (August 22–26, 2022). We are grateful to the participants for their comments and suggestions on an earlier draft. We are also grateful to Yilin Chen and Federico Ninivaggi for their excellent research assistance. We also thank anonymous referees for useful comments. All remaining errors are our own.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.strueco.2023.07.009.

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