

Otto, Anne; Losacker, Sebastian; Hansmeier, Hendrik

Article — Published Version

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The Annals of Regional Science

Provided in Cooperation with:

Springer Nature

Suggested Citation: Otto, Anne; Losacker, Sebastian; Hansmeier, Hendrik (2025) : Relatedness, complexity, and regional development paths in Germany: a sequencing approach, The Annals of Regional Science, ISSN 1432-0592, Springer, Berlin, Heidelberg, Vol. 74, Iss. 2, <https://doi.org/10.1007/s00168-025-01375-5>

This Version is available at:

<https://hdl.handle.net/10419/323677>

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Relatedness, complexity, and regional development paths in Germany: a sequencing approach

Anne Otto¹ · Sebastian Losacker^{2,3} · Hendrik Hansmeier⁴

Received: 25 April 2024 / Accepted: 13 March 2025 / Published online: 5 May 2025
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Abstract

This paper critiques the implementation of the EU's Smart Specialization Strategies (S3), advocating for a deeper analysis of the long-term evolution of regional industrial portfolios. We investigate the changing coherence of these portfolios across 401 German NUTS-3 regions from 1993 to 2018, utilizing skill- and task-based metrics for relatedness and complexity, alongside sequence analysis and optimal matching techniques. We identify various regional trajectory types, enriching the understanding of regional economic development. We find that the majority of regions exhibit a stable coherence of their economic portfolio over time while only a few regions have undergone either more dynamic or fragile development paths. While the selection of priorities in S3 policies is based on the evaluation of the current knowledge base, our findings underscore the importance of historical contexts in regional economic structures, offering insights for enhancing regional diversification strategies and prioritizing capabilities in S3 policy frameworks.

JEL Classification O14 · O25 · O38 · R11

1 Introduction

The Smart Specialization Strategy (S3) is the central approach of European regional innovation policy with a focus on enhancing existing capabilities and venturing into new economic domains to achieve a coherent regional knowledge base. Regions can capitalize on their existing capabilities to develop a coherent industry mix and forge

✉ Anne Otto
anne.otto@iab.de

¹ Institute for Employment Research (IAB), Nuremberg, Germany

² Department of Geography, Justus Liebig University Giessen, Giessen, Germany

³ CIRCLE – Center for Innovation Research, Lund University, Lund, Sweden

⁴ Fraunhofer Institute for Systems and Innovation Research ISI, Karlsruhe, Germany

new competitive advantages in high-value-added activities (Boschma 2017; Foray et al. 2012; McCann and Ortega-Argilés 2015). Major early critiques of S3 were a missing theoretical foundation, lacking tools for effective implementation, and the concern of even growing disparities as peripheral, smaller, and lagging regions might fail in implementing S3 due to limited capabilities (Hassink and Gong 2021).

In the S3 literature, recent theoretical and empirical advancements highlight S3 policies to be related to core concepts of evolutionary economic geography, notably related variety and related diversification (Boschma et al. 2017; Frenken et al. 2007), and stress above all the importance of knowledge complexity (Balland et al. 2019; Boschma et al. 2017; Frenken et al. 2007). Regions with more complex knowledge bases are assumed to be more likely to establish high-value-added activities, and this diversification is expected to be even more beneficial when such activities are closely related to the core knowledge base (Hidalgo and Hausmann 2009; Mewes and Broekel 2020b). Against this background, Balland et al. (2019) developed a specific S3 policy framework. In principle, it works as a policy tool and posits that the closer (or more distant) new potential capabilities are to existing ones, the lower (or higher) the risks involved. The utilization of this tool requires a thorough analysis of the current capability base and its branching potential. The underlying rationales of this framework were evaluated by a set of empirical studies on technological trajectories of EU regions which confirm a positive association of related diversification and growth, particularly for highly complex activities (Balland et al. 2019; Rigby et al. 2022). A second group of studies uses this framework to evaluate S3's adherence and implementation in EU regions. These analyses detect that regional authorities tend to prioritize various domains not necessarily aligned with their capability bases (Buyukyazici 2023; Deegan et al. 2021; Marrocu et al. 2023). However, these evaluations are limited to the actual situation in a region and leave unresolved the question whether S3 strategies are associated with positive economic outcomes as suggested by this framework.

While the practical application of S3 policies within the framework of Balland et al. (2019) resorts to the actual capability base and branching potential of a region, we contend that an effective implementation might be hampered because long-run trajectories are not taken into account. A critical aspect often overlooked is that regions with similar industrial portfolios may follow heterogeneous trajectories due to unique path and place dependencies (Martin and Sunley 2006). In this context, the concepts of 'temporal' and 'geographical wisdom', as discussed by Boschma (2017) and Henning (2019), become particularly relevant. Understanding the long-term formation of a region's economic portfolio could prove to be crucial to gain deeper insights into the current coherence of its capability base. Such understanding is not only relevant for the advancement of S3 diversification strategies but also for their effective implementation. It underscores the importance of incorporating historical and geographical contexts into the analysis and application of S3 policies, ensuring that strategies are tailored to the unique evolutionary path of each region. Moreover, the discrepancies between the S3 guidelines and its practical application in EU regions could stem partly from lacking insights on different types of long-run trajectories and related outcomes for enabling better informed decision-making of regional and national political authorities.

We are committed to addressing these critical issues by introducing a methodology to identify different regional long-run trajectory types and to map systematically the intertwined evolution of regional branching potentials (relatedness density) and complexity. We discern, secondly, whether these regional trajectory types are characteristic for certain socio-economic features and analyze the economic outcomes associated with these development paths. In doing so, we seek to contribute with this methodological approach to an improved applicability of the S3 policy framework proposed by Balland et al. (2019) and effectiveness in guiding regional development strategies.

To this end, we employ this S3 policy framework as our analytical base, with a deliberate emphasis on incorporating a long-term perspective to thoroughly consider historical developments. In more detail, our study analyzes the evolution of the industrial portfolio across 401 NUTS-3 regions (counties) in Germany from 1993 to 2018. To systematically uncover long-term diversification patterns in regions, we utilize sequence analysis techniques. The primary advantage of this methodology is its ability to trace the evolution of the coherence of regional industrial portfolios over time. Additionally, we integrate optimal matching techniques to discern distinct and comparable sequence patterns. To date, the application of these methods in the field of economic geography has been relatively limited (Buch et al. 2022; Hansmeier and Losacker 2024; Kuebart 2022; Losacker and Kuebart 2024). The methodological advancements are complemented by detailed long-term administrative employment data. In a departure from previous S3 literature that predominantly utilized patent data (e.g., Rigby et al. 2022), our approach focuses on the skill and knowledge dimensions of capabilities to encompass a broader range of activities. We utilize a labor-flow based measure of skill-relatedness and the industry space (Neffke et al. 2017), as well as the complexity level of tasks within industries. In addition, we resort to a broad set of socio-economic indicators for comparing the characteristics of different development paths and related economic performance.

The remainder of the paper is structured as follows. In Sect. 2, we sketch the theoretical background and relevant literature on regional trajectories, relatedness and complexity. In Sect. 3, we introduce the data base, and indicators for relatedness and complexity, and how we apply sequence and cluster methods in our empirical analyses. We present our findings on regional sequence patterns in Sect. 4, and Sect. 5 concludes with a discussion.

2 Theoretical background and related literature

Recent research in economic geography and regional studies has emphasized the importance of systematic empirical evidence in the effective operationalization and implementation of Smart Specialization Strategies (S3) within European regions. This evidence is crucial in understanding how regions can maintain a competitive advantage and improve their economic portfolio over time. The concept of related diversification is particularly relevant in this regard, aligning closely with these concepts (Boschma 2017; Marrocu et al. 2023; Mewes and Broekel 2020b; Rigby et al. 2022). Against this background, Balland et al. (2019) underscore the necessity

for S3 to integrate both relatedness (Hidalgo et al. 2007, 2018; Neffke et al. 2011), and complexity (Balland et al. 2022; Hidalgo and Hausmann 2009). These elements are instrumental in shaping the selection of new potential capabilities that regional policy actors should prioritize.

Capabilities encompass a wide range of local assets, including natural resources, infrastructure, institutions, technologies, knowledge, and skills (Frenken et al. 2023; Maskell and Malmberg 1999). Contemporary research focuses on identifying which capabilities hold the key potentials for regions to branch into new areas, thereby offering new opportunities for regional development. A prevalent theme across numerous quantitative studies is the observation that diversification often gravitates toward activities related to pre-existing ones. This trend suggests that regional developmental paths are deeply rooted in territorial capabilities (Boschma 2017). Regional diversification is conceptualized as a branching process, where new activities evolve from the synergy of related existing ones (Fornahl and Guenther 2010; Frenken et al. 2007). However, regions with a limited range of activities or those with inadequate capabilities may struggle in forging new specializations. A substantial body of scholarly research provides empirical evidence of related diversification contributing to the growth of industrial clusters, regions, and countries, as well as determining workers and firms. Boschma (2017) emphasizes that this phenomenon is evident regardless of employed variables (e.g., products, industries, technologies), relatedness measures, spatial levels, or observation periods. Activities are considered related when they utilize similar resources (Frenken et al. 2023; Hidalgo et al. 2018). The existing portfolio of related capabilities is crucial for a region to develop new activities (Neffke et al. 2011) and in determining which new activities are likely to emerge, thus shaping path-dependent regional trajectories (Content and Frenken 2016).

Deegan et al. (2021) suggest that the propensity of a region to initiate new activities or abandon existing ones can be interpreted as an assessment of risks associated with diversification policies. They argue that the probability of failure for regions increases when diversification ventures into domains that are unrelated to their current economic portfolio. Mewes and Broekel (2020a) further illuminate that relatedness can sometimes lead to market failures, necessitating intervention. Such situations may arise when a region aims to develop new related activities but is hindered by limited or absent capabilities.

The concept of economic complexity is pivotal in this discourse. It posits that certain economic activities are inherently more complex than others. Regions or countries that specialize in these complex economic activities typically tend to be more competitive than those lacking the capacity to engage in complex activities (Hidalgo and Hausmann 2009). Indeed, economic complexity has been identified as a key predictor of economic prosperity, income, and other indicators of economic development, surpassing traditional predictors like governance or institutional quality (Balland et al. 2022; Hausmann et al. 2014). Recent research in economic geography and regional studies corroborates that the advantages of engaging in complex activities are equally pivotal at the regional level (Mewes and Broekel 2020b; Pintar and Scherngell 2022). Concurrently, there is an expanding body of literature indicating that complex economic activities tend

to be geographically concentrated, thereby becoming a driver of inequality. This phenomenon is observable not only in exports, but also in complex occupations, industries, and technological innovations (Balland et al. 2020; Balland and Rigby 2017). Therefore, regions are encouraged to strive toward diversification into complex activities. Such a strategic shift can lead to the upgrading of the local industry mix, fostering competitive advantages and stimulating economic growth (Balland et al. 2019).

Balland et al. (2019) put forth a compelling argument that relatedness and complexity should be fundamental elements in S3 policy. They devised a framework designed to assist policy actors in identifying potential opportunities for regional diversification, aimed at enhancing the region's knowledge base. This framework focuses on capabilities that, although not currently among a region's specialized strengths, are intricately connected to its existing economic portfolio. Diversifying into activities that are highly complex can substantially enrich a region's overall complexity, thereby augmenting its local capabilities. The more distant a new activity is from the existing capabilities, the greater the risks associated with such a diversification strategy.

In their framework, Balland et al. (2019) differentiate between different regional diversification opportunities for S3 policy in a scheme along the two dimensions complexity and relatedness (Fig. 1). A diversification of the knowledge base into related high-complex activities is proposed as benchmark strategy with low risks to improve over the long-run a region's coherence of capabilities and competitiveness. A further advantageous strategy, but associated with a high failure risk, may be the diversification into high complex, but unrelated activities due to missing links to local knowledge resources. In turn, the establishment

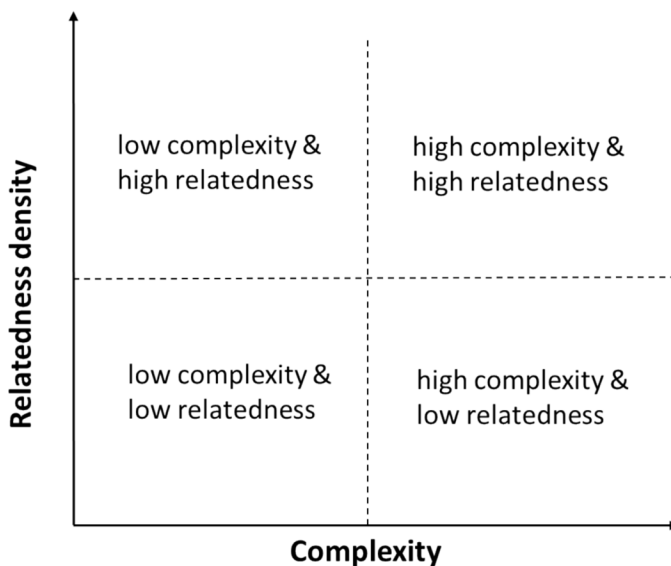


Fig. 1 Smart specialization framework (based on Balland et al. 2019)

of low complex activities either strongly related or even unrelated to the existing capabilities are not expected to fundamentally enhance a region's knowledge base.

The small number of studies having empirically evaluated this framework so far focus either on the underlying rationales or on the congruence between the practical implementation of S3 policies and European Union guidelines. In the same paper, Balland et al. (2019) use historical patent data for EU regions, demonstrating that relatedness positively impacts diversification, particularly when technologies are closely aligned with the existing knowledge base. Rigby et al. (2022), studying technological trajectories of 145 cities in the EU, find that city growth accelerates when there is a specialization in complex technologies closely related to local capabilities. Balland and Boschma (2021), examining inter-regional linkages, detect that especially peripheral EU regions with complementary capabilities have an increased likelihood to diversify. However, Pinheiro et al. (2022) observe that economically prosperous regions in the EU tend to diversify into related, high-complex domains, while structurally weaker areas do not follow this pattern.

A second group of studies evaluated how closely regional authorities adhere to and implement S3 policies in accordance with European Union guidelines. Deegan et al. (2021) reveal that local authorities in various EU regions tend to select either related or complex domains for specialization, but rarely both, as is recommended in the S3 framework by Balland et al. (2019). Buyukyazici (2023) observes for Italian regions that more prosperous areas often choose related, but less complex domains, while lagging regions prioritize unrelated ones. For EU and Italian regions, Marrocu et al. (2023) and D'Adda et al. (2019) found that the selection of target domains is often both less related and not congruent with existing specializations, resp. Di Cataldo et al. (2022) stress that S3 priority sets in political practice are often less selective, leading to underutilized potential of such regional innovation policies.

The first group of evaluations thus provides empirical findings which confirm, by and large, the underlying reasoning of the framework of Balland et al. (2019). Although the second group of evaluations uses this framework to assess the alignment and implementation of S3 policies with European guidelines, these studies are limited to the actual regional context. Further, these evaluations have paid only little attention to the question whether regions benefit from S3 strategies within this framework in terms of positive economic outcomes. We contend that the establishment of comprehensive S3 policy strategies should be based upon insights on long-run trajectories and outcomes. As the current iteration of the S3 framework, as formulated by Balland et al. (2019), focuses solely on a region's actual industrial portfolio to identify potential diversification opportunities, we provide a methodology to map diverse regional pathways in the long-run, thereby enriching the framework's applicability and effectiveness in guiding regional development strategies. Then, we apply this methodology to identify different regional trajectories and evaluate the structural features and economic outcomes of these trajectory types.

3 Empirical strategy

3.1 Data

We resort to the German Employment History database (henceforth: EH) of the Institute for Employment Research (IAB) for displaying the measures of inter-industry skill-relatedness, relatedness density and industry-specific complexity. The EH comprises all employees and apprentices who are required to make social security contributions as of June 30th of a given year. Civil servants, self-employed persons and regular students are not part of the social security system and therefore not reported in the EH. For West Germany, information on employment is included from 1975 onward and for East Germany from 1993. The EH comprises socio-demographic information on each employee as well as employment-specific information (e.g., occupation, wage, type of employment). This information on employees can be linked to employer data (e.g., industry and location of establishments). Hence, this data base enables us to trace individual job moves between establishments of different industries. The EH contains a consolidated industry coding system that assigns to each establishment and thus employees imputed classification codes from 1975 onward which are consistent with the NACE Rev. 2 (Vom Berge et al. 2013).

3.2 Measures of relatedness, relatedness density and complexity

Since S3 studies on relatedness use mainly measures of technological relatedness based on patent data, specializations in non-technological domains, which could open up new trajectories, remain underexplored (Balland and Boschma 2021; D'Adda et al. 2019; Kogler et al. 2023; Rigby et al. 2022). We look at knowledge and skills required to conduct job-specific tasks to capture regional capabilities. We resort to the labor-flow based measure of skill-relatedness (Neffke and Henning 2013), thereby covering a broader range of activities such as utilities, tourism, and health/social services. Buyukyazici et al. (2023) stress that skills and capabilities have received increased attention in regional innovation policies. In line with this, funding in the current ERDF period 2021–2017 aims to induce skills for smart specialization (European Parliament, Council of the European Union 2021).

3.2.1 Inter-industry skill-relatedness

To display an inter-industry skill-relatedness (SR) indicator, we employ the method of relative risks (Neffke et al. 2017). Based on the EH database, we derive the number of job switches of full-time employees (18–65 years) between 3 digit-industries and display an averaged matrix of the SR indicator for the period 2012/2013 to 2015/2016 (288×288 3-digit industry pair combinations). More detailed information is provided in Appendix 2.

3.2.2 Relatedness density of regions

Based on this SR-matrix, we construct the German industry space as a network of industry pairs i and j as nodes and the degree of relatedness between those industries as links (ϕ_{ij}). We follow Balland et al. (2019) and compute the average relatedness density for each region r to measure the coherence of the regional industrial portfolio. The density for an industry i in region r is based on the relatedness ϕ_{ij} of industry i to all industries j in which the region features a comparative advantage, divided by the sum of the relatedness of industry i to all other industries j in Germany. The relatedness density (RD) is thus given by:

$$RD_{ri} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} \times 100$$

The comparative advantage is dichotomized with 1 for a relative advantage (RCA) of region r in industry i if the share of employees (emp) in this industry is relatively larger than in the reference region (Germany) and 0 if not. It can be denoted as

$$RCA_{ri} = \frac{\text{emp}_{ri} / \sum_i \text{emp}_{ri}}{\sum_r \text{emp}_{ri} / \sum_r \sum_i \text{emp}_{ri}} > 1$$

The average relatedness density can be used to describe a region's potential to branch into new industries. This indicator has proven to be a good predictor of the probability that a new economic activity will be established in a region (e.g., Hidalgo et al. 2018). Figure 2 shows the average relatedness density (1993–2013) for NUTS-3 regions in Germany. Relatedness density is lowest in counties with a big local enterprise such as car manufacturers in Wolfsburg (Volkswagen) or Ingolstadt (Audi). A great branching potential is observed in a range of agglomerations such as Stuttgart, Hamburg, Cologne or Munich, but this does not apply to all of those (e.g., Berlin, Bonn, and Ruhr area). Yet, diversification potential is highest in suburban counties around Frankfurt and Munich.

3.2.3 Complexity of regions

Up to now, no indicator of economic complexity has been established as state of the art (e.g., Broekel 2019). Although the Economic Complexity Index (ECI) (Hidalgo and Hausmann 2009) has been widely employed in regional research and economic geography, Broekel (2019) criticizes that this index is rather an indirect measure of complexity and has proven to be problematic when being applied to European datasets. Instead, we relate to a complexity measure from labor economics which has been recently used in economic geography by Deegan et al. (2021) and Lo Turco and Maggioni (2022). We rely upon the concept of (occupational) task complexity introduced by Caines et al. (2017). They define complex occupational tasks as those requiring higher-order skills, such as “the ability to abstract, solve problems, make decisions, or communicate effectively” (Caines et al. 2017, p. 299). Their

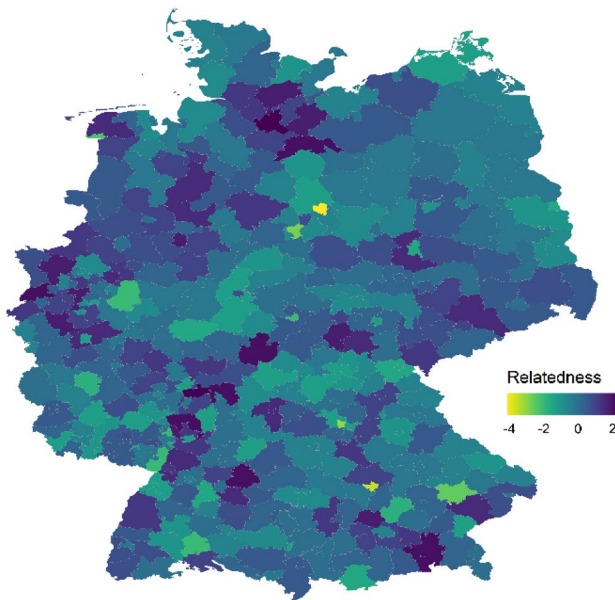


Fig. 2 Average relatedness density (branching potential) (1993–2018), normalized, NUTS-3 regions, Germany. (Source: Employment History, own calculations)

study uses information on 35 complex tasks from the Occupational Information Network (O*NET) and applies principal component analysis to derive a complexity measure describing the extent to which occupations are based on complex tasks. This study finds that complex occupations are positively linked to wage levels and wage growth in the USA; thus, such professions are related to favorable economic outcomes. Deegan et al. (2021) employ a concordance to adapt this US occupational complexity measure to European data. Then, they assess the average complexity of an industry relying on its occupational employment structure. In line with this work, we measure the average task complexity of regional industrial portfolios. We resort to occupational complexity task information provided by the German Classification of Occupations (*Klassifikation der Berufe, KldB 2010*; henceforth: KldB 2010) which has been widely used in (regional) labor market research in Germany (e.g., Gathmann et al. 2024; Meister et al. 2023). This classification assigns to each of the approximately 1,300 occupations (5-digit level) a degree of task complexity. The underlying conjecture is that the more complex the tasks in an occupation, the longer periods of formal (vocational) education or informal working experience and higher levels of knowledge and skills are required. The KldB 2010 assigns one of the following four task complexity levels to each occupation: Unskilled/semiskilled occupation (1), specialist occupation (2), complex specialist occupation (3) and highly complex occupation (4). These highly complex tasks are for instance R&D tasks, diagnostic activities, imparting of knowledge as well as management and leadership tasks. In turn, unskilled/semiskilled occupations rely on simple (routine) tasks (Paulus and Matthes 2013). We use the task complexity levels defined for

occupations in 2018, translate this indicator to the industry level and calculate the average complexity-level for each region over time based on the distribution of employees over all industries in the region in a given year. The average complexity (AC) of a region is thus given by

$$AC_r = \frac{\sum_r(\text{emp}_{ri} \times \psi_i)}{\sum_r \text{emp}_{ri}} \times 100$$

with ψ_i denoting the average task complexity-level of industry i , ranging from 1 to 4. We provide the average complexity values for selected industries in Table A-1 in Appendix 1. It should be taken into account that our measure of occupational task complexity reflects to a significant degree the human capital concept. However, this applies also to other economic complexity measures, as complex economic activities typically require high levels of human capital. In this regard, our measure is more aligned with the input side of complexity, assessing the skills needed to perform (complex) tasks, while measures like the Economic Complexity Index (ECI) focus on the output side of complexity, evaluating the complexity of already manufactured products, such as those captured through trade data or patents (Broekel 2019).

Figure 3 depicts the average industrial complexity over the observation period for NUTS-3 regions in Germany. Urban agglomerations such as Stuttgart, Munich, Berlin, Hamburg and the Ruhr area host the highest complex industrial portfolios. Many regions in Southern Germany are also marked by a high complexity being specialized in different manufacturing industries such as automobile, machinery, aircraft or

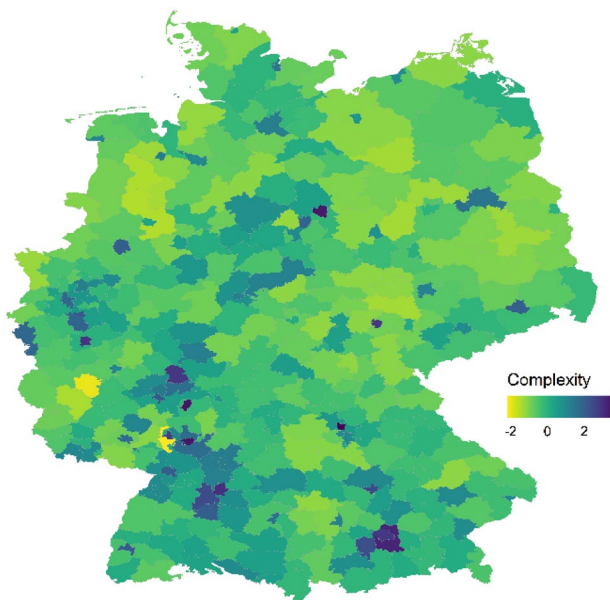


Fig. 3 Average industrial complexity (1993–2018), normalized, NUTS-3 regions, Germany. (Source: Employment History, own calculations)

microelectronics. Less densely populated rural regions being farther away from the urban agglomerations show a less complex industrial portfolio whereby these regions even appear to have a more complex industry mix in Southern Germany compared to the Northern part.

3.3 Sequence analysis and hierarchical clustering

Sequence analysis is a rich set of methods, originating from bioinformatics to analyze DNA strings. Andrew Abbott (1995) introduced the method to social sciences in a seminal paper and proposed to study career paths using these techniques. Meanwhile, it is now a well-established method in sociology, education and employment research, demographic research and related fields. Nevertheless, applications in economic geography, regional studies and related spatial disciplines are limited (for exceptions, see Buch et al. 2022; Hansmeier and Losacker 2024; Kuebart 2022; Losacker and Kuebart 2024).

Sequence analysis processes categorical longitudinal data, where sequences refer to ordered states for each unit of observation over time. More formally, a state sequence of length l is an ordered list of l elements (states) chosen from set A . Hence, a sequence x can be denoted as a vector of states $x = (x_1, x_2, x_3, \dots, x_l)$, with $x_j \in A$. State sequences feature two characteristics. First, states cover a specific period of time opposed to events that represent a specific point in time. Second, the position of each state provides information on the absolute or relative period of time within the respective sequence and in between all sequences in the dataset (Cornwell 2015; Liao et al. 2022). Given this structure for a balanced panel with N observations and T time periods, the number of observed states n equals $N \times T$.

Sequence analysis comprises a range of statistical and graphical tools to exploit this kind of data. Therefore, sequence analysis is not to be understood as a single method but rather as a 'collection of techniques' (Abbott 1995, p. 93). For instance, sequence analysis can be used to visualize sequence data in order to examine structures and to identify frequent states or frequent transitions. Next to basic descriptives, optimal matching techniques can be employed to detect clusters of sequences (Abbott and Tsay 2000; Cornwell 2015; Liao et al. 2022).

For the empirical part of this paper, we use regions as observation units and define the set of states based on the combination of low/high average relatedness density and low/high average complexity of the regional industrial portfolio (see Fig. 4). We use the median relatedness and complexity values in 2018 as thresholds to distinguish between low and high states. To test the robustness of our major results, we adjust this threshold, using other quantiles (e.g., 60%, 70%). We thus define four states and assign these states to the 401 NUTS-3 regions from 1993 to 2018, resulting in a sequence of 26 states for each region.

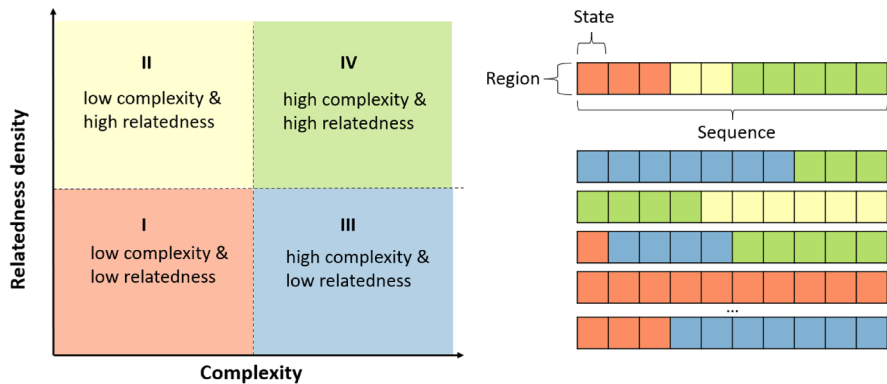


Fig. 4 Operationalization of state sequences using the smart specialization framework (based on Balland et al. 2019)

4 Empirical results

4.1 Clusters of regions with similar sequence patterns

The full sequence index plots for all regions (Fig. 5) illustrate the heterogeneity of regional trajectories and reveal that the regions have become on average more complex and more coherent in terms of average relatedness density. In Fig. 5, the left plot visualizes the full sequence data (random order), while the other two plots visualize regional trajectories sorted by first state (middle panel) and last state (right

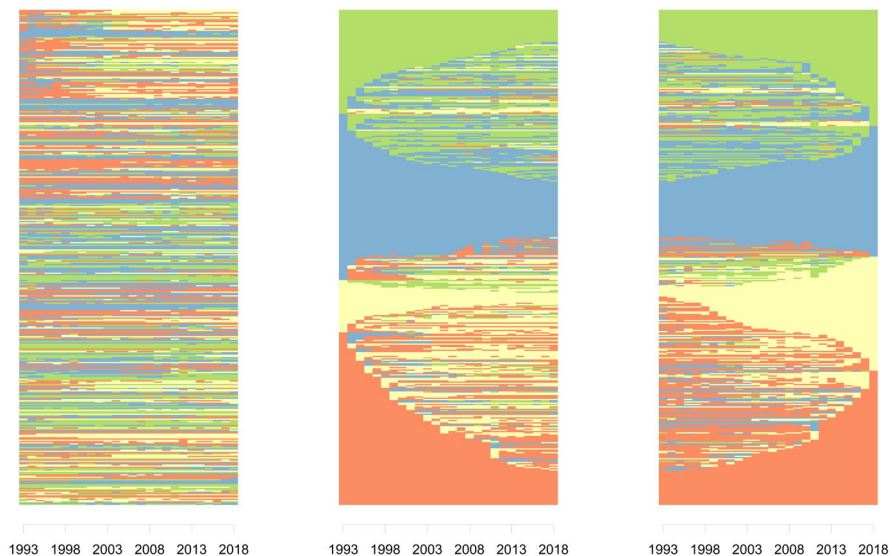


Fig. 5 Raw sequence plots of relatedness and complexity of the regional industrial portfolio. (Source: Employment History, own calculations)

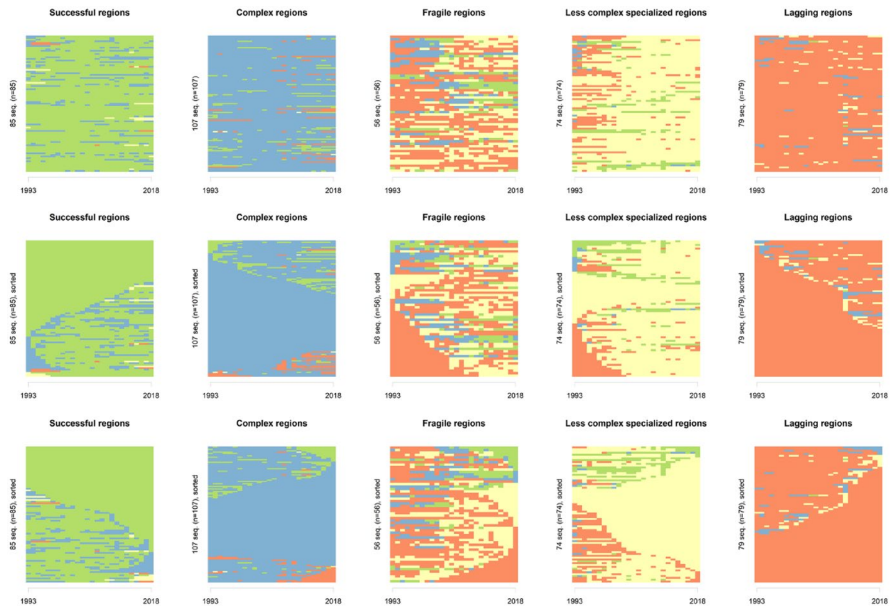


Fig. 6 Clusters with similar sequence patterns of relatedness and complexity of the regional industrial portfolio. (Source: Employment History, own calculations)

panel). While sequence index plots are helpful to visualize the diversity of regional trajectories, they do not reveal (statistical) similarities between distinct trajectories.

In order to unveil similar developmental trajectories of regions, we clustered regions based on optimal matching techniques. Optimal matching compares all sequences by finding the minimal costs of insertions, deletions and substitutions of states, and computes statistical distances between all sequences (Studer and Ritschard 2016). Based on these distances, we employed a ward algorithm for hierarchical clustering. We thus developed a typology that allows a more detailed analysis of different regional paths in light of complexity and relatedness. This led to five final clusters, i.e., five different types of regional trajectories: (1) successful regions, (2) complex regions, (3) fragile regions, (4) less complex specialized regions, and (5) lagging regions.¹ The size of the clusters ranges from $n = 55$ (fragile regions (3)) to $n = 107$ (complex regions (2)). The cluster types exhibit significant variation in the stability (or fragility) of their regional trajectories; the average number of transitions (changes in states over time) differs markedly. Regions in cluster type 3 (fragile regions) average 7.2 transitions from 1993 to 2018. The most stable clusters are complex regions and lagging regions, with only 2.1 and 2.0 transitions, respectively. In comparison, successful regions (3.0 transitions) and less

¹ The choice of five clusters was the best solution with regard to cluster size, theoretical interpretability as well as change in cluster heterogeneity. However, we also considered solutions with four and six clusters.

complex specialized regions (3.9 transitions) show more instable trajectories. The typology is shown in Fig. 6, following the sequence index plotting techniques from Fig. 5. To check whether these clusters of different regional pathways are consistent, we conducted a set of additional sequence and cluster analyses. For instance, we used different thresholds for constructing the sequence states (i.e., n -quantiles), we used different distance measures for the cluster analysis (i.e., longest common prefix, longest common subsequence), we used different indicators to measure relatedness (i.e., correlation-based measures) and complexity (i.e., substitution potential of jobs (share of routine tasks in occupations (Dengler and Matthes 2018))), and we tested for sensitivity to data transformations (i.e., log transformations). Overall, the major results presented in this paper are robust against these adaptations. Figure 7 shows this typology of regional clusters in a map.

In the following paragraphs, we first describe the sequence patterns in each of the five regional clusters. Then, we examine whether the regions in these clusters are characterized by different structural characteristics and economic outcomes.

Cluster type 1 comprises *successful regions* that have a very coherent industry portfolio with complex capabilities. These regions maintained a complex economic structure offering diversification opportunities into new industries. A great range of large urban agglomerations makes up this cluster, including Berlin, Dusseldorf, Hamburg, Cologne, Munich, Leipzig, and Dresden, but also most cities in the Ruhr area.

Cluster 2 consists of *complex regions* with a highly complex industry mix, but a weak coherence. This state did hardly change over time, and this applies to almost

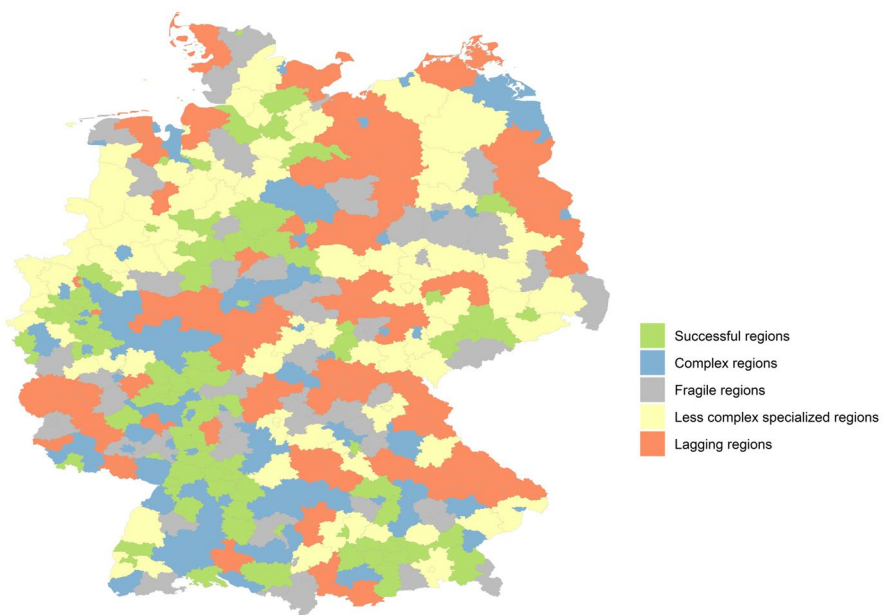


Fig. 7 Map of the clusters, NUTS-3 regions, Germany. (Source: Employment History, own calculations)

all regions in this cluster. Having had only a weak branching potential over time, these regions had presumably rather limited opportunities to diversify the complex industrial portfolio into related activities. This cluster includes numerous bigger and medium-sized cities in East Germany (e.g., Rostock, Schwerin, Jena, and Gera) and in West Germany (e.g., Kaiserslautern, Ludwigshafen, Kiel, and Ingolstadt), but also in rural areas in South-West Germany (e.g., Southern Baden-Württemberg).

Development paths in the clusters 3 and 4 are less consistent. In cluster 3, the *fragile regions*, sequence patterns are rather unstable due to many changes between the four states. These regions seem to be less path-dependent. Nevertheless, we detect a considerable number of regions that keep their less complex knowledge base, but established a more coherent industrial portfolio. These are, for instance, medium-sized cities and their surrounding areas in rural regions such as Trier and Weimar, but also some suburban areas of Berlin. While this category captures a variety of unique regional trajectories, it is also a residual category, encompassing all sequences not aligning with the stable clusters.

The *less complex specialized regions* in cluster 4 are characterized by a low complexity of the industrial portfolio, but a high relatedness density. These regions are located mainly in rural and peripheral areas in Northern and Eastern Germany. A few of these regions have succeeded in catching-up by increasing the average complexity of their economic activities, thus transitioning to state IV (high complexity, high relatedness). A small set of regions in this cluster was initially characterized by both a low complexity and low relatedness density, but managed to leverage their branching potential, thus transitioning from state I to state II.

Finally, cluster type 5 comprises *lagging regions* that have limited capabilities of improving either the average relatedness or complexity of their economic activities. In these regions, the level of these two indicators has remained at a low level throughout the entire observation period. These are structurally weak regions in Germany: the coastal regions, border regions (e.g., at German-Polish border and at the German-Czech border), and more peripheral rural areas (e.g., Northern Hesse and Eifel).

To understand whether there are differences in structural characteristics among regions belonging to one of the five clusters, we compare a broad set of socio-economic indicators across these cluster types (see Fig. 8). These regional indicators are sourced for the year 2018 from the INKAR database, provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). One-way ANOVAs reveal significant ($p < 0.05$) differences between group means of the five cluster types for all chosen indicators, with the exception of the unemployment rate. Regions in cluster types 1 and 2, on average, have larger populations and higher population densities compared to those in other cluster types. These clusters, identified as successful and complex regions, are predominantly composed of more densely populated urban areas. Furthermore, regions in these two cluster types exhibit, on average, higher values for indicators such as GDP per capita, the proportion of university degree holders, and the number of patents. The opposite is true for the unemployment rate. This indicator is, on average, higher in the successful cluster (type 1) and complex cluster (type 2) than in the fragile cluster (type 3) and lagging cluster (type 5). Cluster types 1 and 2 comprise various urban agglomerations,

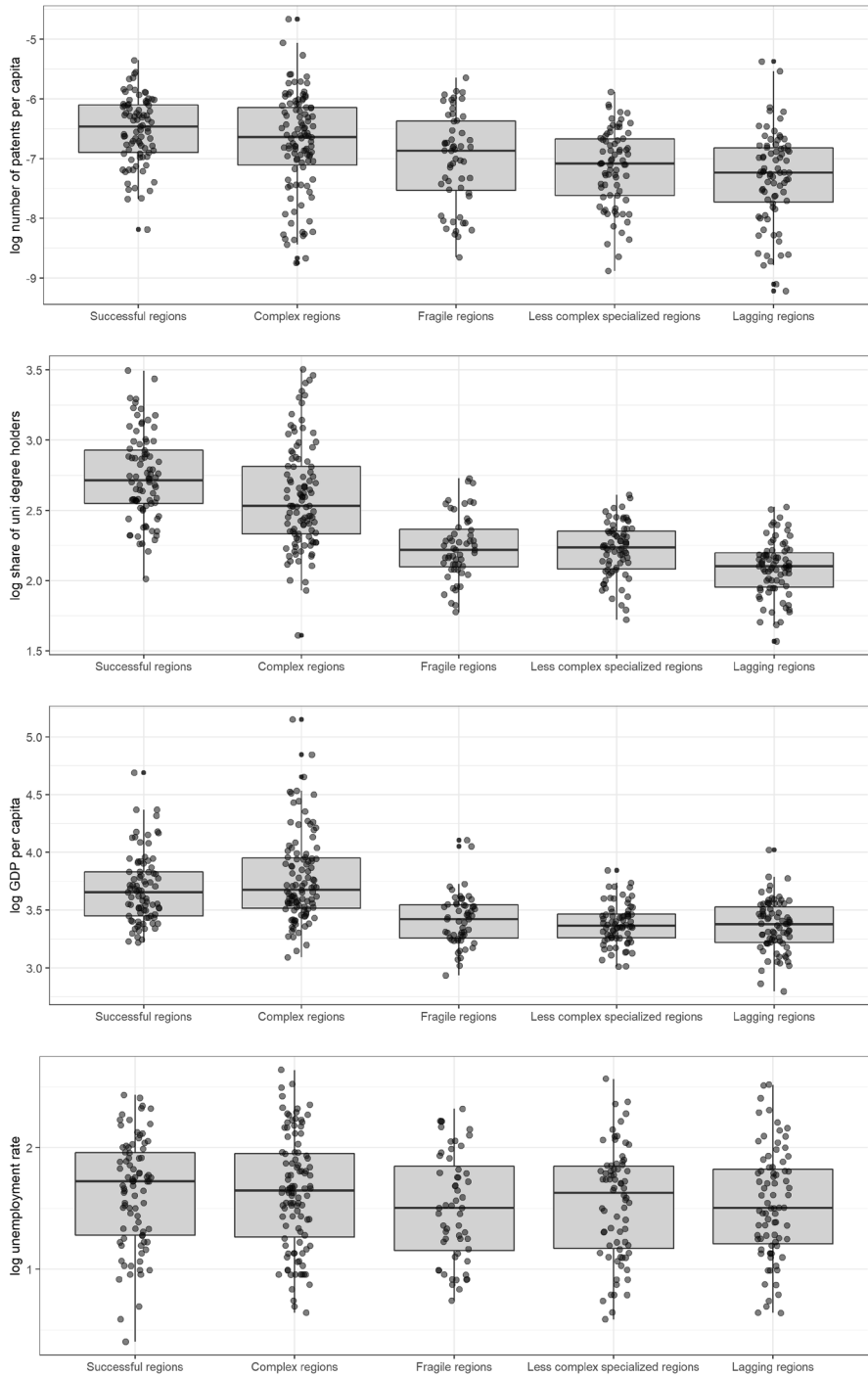


Fig. 8 Descriptive indicators of the clusters in 2018 (Source: Employment History Panel (EH), INKAR database of the BBSR, own calculations)

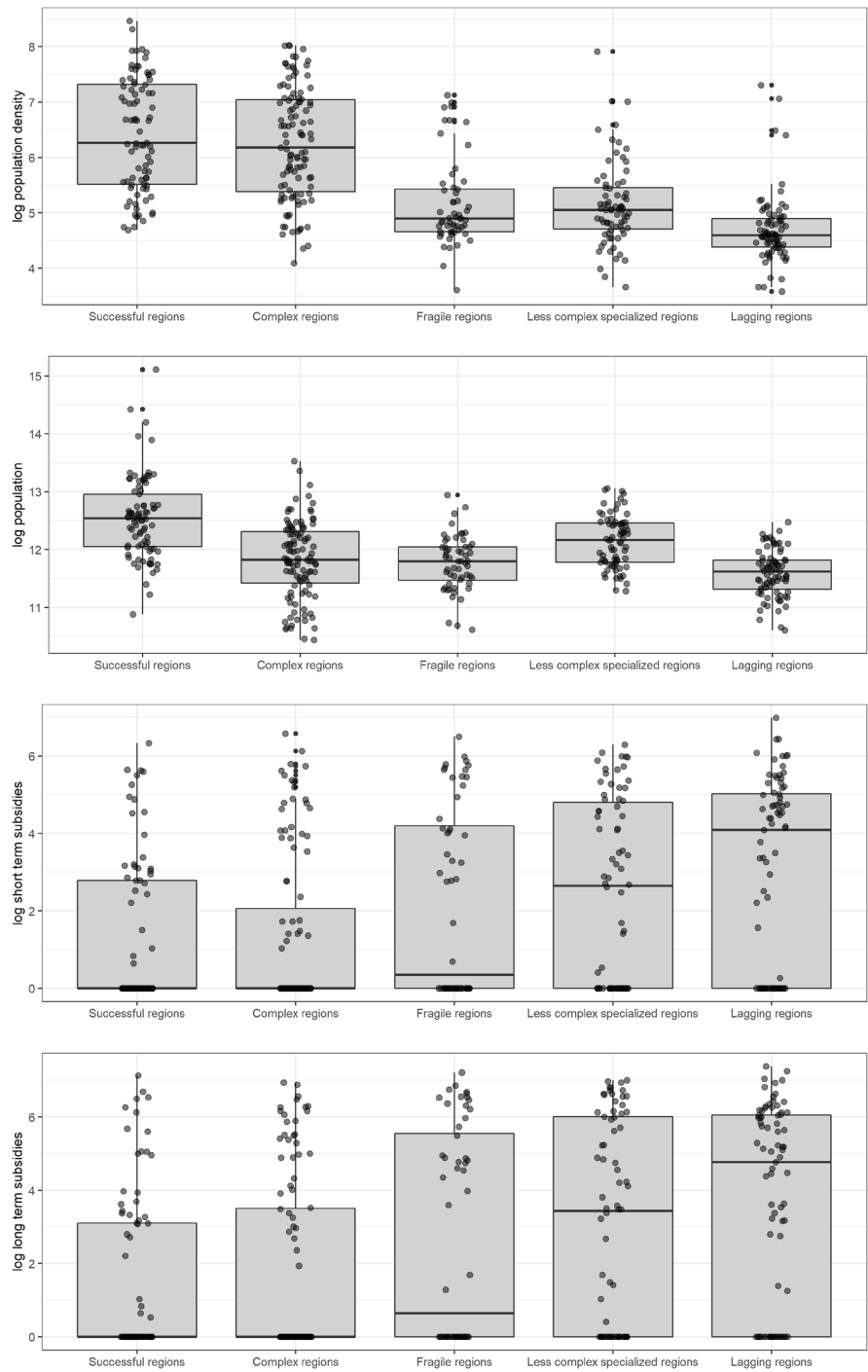


Fig. 8 (continued)

population groups furthest from the labor market (e.g., migrants and older workers) are more concentrated in these areas. These workers often have to overcome greater barriers to take up employment. The fragile cluster (type 3) is in a “middle position”. This cluster exhibits slightly larger average values for patents per capita and GDP per capita than in the less complex and lagging cluster (types 4 and 5), resp. In addition, fragile regions have received just a little more short- and long-term subsidies compared to the successful and complex cluster (types 1 and 2). This discrepancy is much larger for less complex and lagging cluster regions (types 4 and 5).² This finding indicates that cluster types 4 and 5 comprise more structurally weak areas depending on external public support for regional development.

While the previous analyses showed how different regional sequence patterns (clusters) relate to socio-economic regional conditions at the end of the observation period (2018), we elucidate in a next step the relationship between these trajectories and long-term changes in regional economic outcomes. Therefore, we examine how changes in GDP per capita and unemployment rates over the observation period differ across clusters. Specifically, we compare the changes from the beginning of the observation period (average of 1993 and 1994) to the end (average of 2017 and 2018) for both variables, and we present these changes by cluster (see Fig. 9). We observe that complex cluster regions (type 2) exhibit on average the strongest GDP per capita growth, closely followed by the successful cluster (type 1). GDP per capita growth is less strong in the three other clusters, resp. Most notably, average economic growth in the fragile cluster (type 3) is on average slightly higher than in less complex and lagging cluster regions. The decline in unemployment rates is strongest in successful and complex cluster regions. This decrease is less pronounced in the other three clusters, but slightly stronger in the less complex cluster (type 4).

In addition, we conducted one-way ANOVAs revealing significant differences ($p < 0.05$) between the group means of the five cluster types for both indicators. Given the significance of the overall models, we employed a Tukey HSD post hoc test to investigate pairwise differences between clusters. For changes in GDP per capita, the post hoc analysis reveals significant differences ($p < 0.05$) for all pairwise comparisons, except between less complex specialized regions and fragile regions, lagging regions and fragile regions, and lagging regions and less complex specialized regions. This post-hoc analysis for changes in unemployment rates showed significant differences ($p < 0.05$) between successful regions and fragile, less complex specialized, and lagging regions, as well as between complex regions and less complex specialized and lagging regions.

These descriptive findings indicate that socio-economic conditions and economic performance appear to be more favorable in the successful and complex cluster than in less complex and lagging regions. The “middle position” of fragile regions

² Subsidies include approved grants with co-financing for business activities or infrastructure measures within the framework of the German “Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur (GRW)”. These encompass contributions from federal, state, and the European Regional Development Fund (ERDF). Typically, such subsidies are allocated to structurally weak regions, often those below the EU average GDP, explaining why several regions did not receive any subsidies (see Fig. 8).

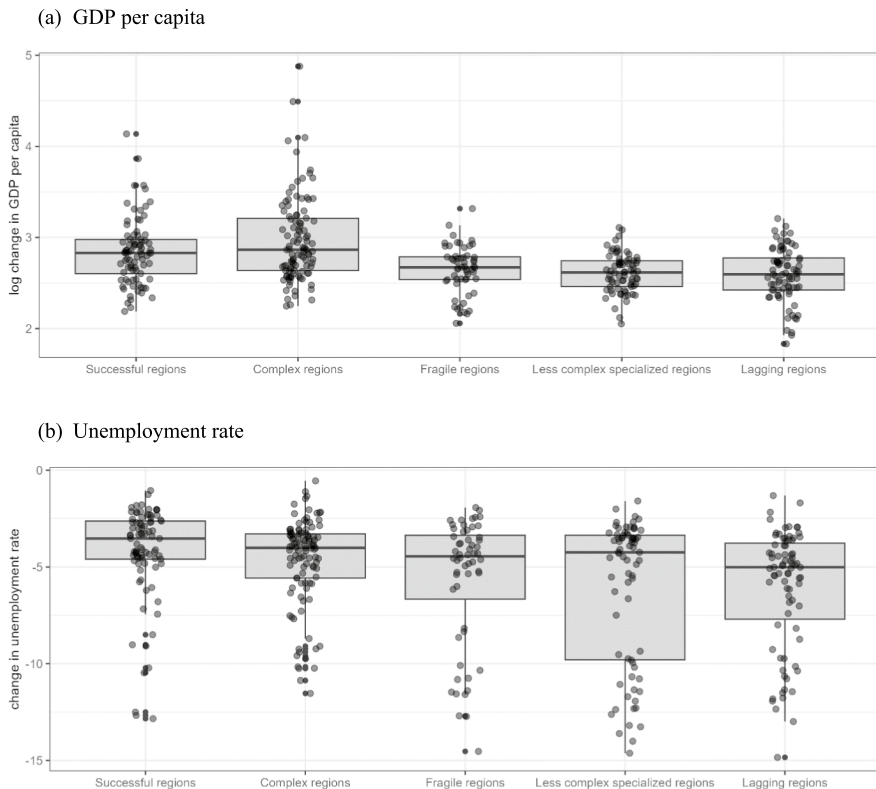
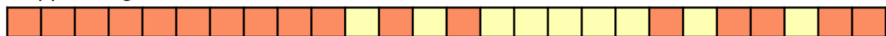


Fig. 9 Outcome indicators of clusters—changes of average values between 1993/1994 and 2017/18 (Source: Employment History Panel (EH), INKAR database of the BBSR, own calculations)

Worms



Cloppenburg



1993

2018

Fig. 10 Sequence pattern of Worms and Cloppenburg

in terms of regional conditions and economic growth points to the diverging trajectories in this cluster type—including also changes in quadrants in the smart specialization framework of Balland et al. (2019) (see Fig. 4).

4.2 Mini case studies

For a more detailed examination of such dynamic trajectories, we selected two NUTS-3 regions from the fragile cluster (type 3), namely Worms and Cloppenburg

(Fig. 10). These mini case studies focus on changes in the complexity and branching potential (relatedness density). We compare first the employment structure in sectors with low (and high) complexity between the beginning and end of the observation period. Then, it is examined how relatedness density in less and more complex industries has evolved in the long-run. Here, we highlight the main results, while detailed information on the mini case studies is provided in Appendix 3.

Starting in the nineteenth century, the city of Worms has specialized in the emerging chemical industry due to its location on the Rhine River. The more recent sequence pattern of this city shows a rather continuous development path, transitioning from a highly complex industrial mix with substantial branching potential (state IV) to a less complex industry mix characterized by low diversification potential (state I) (see Fig. 10). In Worms, less complex industries have become more significant in terms of employment, but diversification opportunities into these economic activities (location coefficient < 1) deteriorated over time. Many of these less complex industries have become more distant from the economic core. In turn, more complex industries are nowadays better embedded. In Appendix 3 Fig. A-2a demonstrates that the number of favorable opportunities for further specialization in closer connected less and more complex industries is limited, but the majority of diversification options is found in less complex industries being only weakly connected, offering less advantageous possibilities for leveraging the regional knowledge base.

In north-western Germany, the county of Cloppenburg is part of the Oldenburger Münsterland which evolved since the Second World War into one of Europe's most efficient agricultural economic zones with a focus on intensive livestock farming and a specialization in agricultural technology. This region hosts numerous companies specializing in the development, production, and marketing of animal husbandry equipment (Klein and Tamasy 2021). Despite dynamic employment growth in both less and more complex industries, Cloppenburg's industrial portfolio remained mainly focused on more simple activities. The coherence of its industrial portfolio increased, indicating an enhancement in local diversification opportunities. The closeness of industries from various sectors, both less and more complex (with a location coefficient < 1), to the agricultural economic core has increased. In Fig. A-4a, it is evident that numerous opportunities for further specialization in both less and more complex activities across a diverse range of sectors have emerged in this region. These diverging trajectories are mirrored by different economic outcomes with an increase in GDP per capita and a decline in unemployment above (below) national average trends in Cloppenburg (Worms) throughout the observation period.

5 Discussion and conclusion

The objective of this study was to provide a methodological approach for improving the applicability of the Smart Specialization Strategy (S3) framework of Balland et al. (2019) and thereby enabling more adequate designs and implementations of regional development strategies. For this purpose, we complement this framework with a long-term dimension to account for diverging trajectories when assessing

a region's diversification opportunities. For 401 NUTS-3 regions in Germany, we examined the co-evolution of their branching potential and complexity from 1993 to 2018. We utilized sequence analysis and optimal matching techniques to identify cluster types with a high similarity of sequential patterns. We find that most regions in Germany belong to four clusters showing stable trajectories. These paths are marked by a maintenance of either a low (high) average relatedness density and/or low (high) average complexity over time. In general, these outcomes point to rather cemented spatial inequalities in Germany. The comparison of structural features revealed that socio-economic conditions and economic performance appear to be more favorable in the successful and complex cluster regions than in less complex and lagging regions. The successful and complex clusters comprise each densely populated, economic prosperous and innovative regions and exhibit greater economic performance while those concentrated in the lagging and less complex specialized cluster types depend to a much greater extent on subsidies and show lower economic growth. These results point to better growth opportunities in regions with a complex industrial portfolio, even if this remains rather stable over time, as suggested by the sequence analysis. The small fragile cluster has a "middle position" between the less and better performing cluster types, and encompasses primarily instable unique trajectories. Two mini case studies from this cluster exemplify how both the coherence and complexity of an industrial portfolio can evolve over the long term, thereby determining opportunities for diversification. These findings of our paper suggest in several ways that it is recommendable to consider long-term development paths and geographical contexts when implementing S3 policies.

Firstly, we found two big clusters—low complex specialized (cluster 4) and successful regions (cluster 1) in which regions managed to keep a strong coherence of the industrial portfolio and diversification opportunities into either simple or more complex activities. Particularly the low complex specialized regions did not achieve to enter more complex activities. Pinheiro et al. (2022) show that a region's closeness to more complex activities facilitates the cumulation of capabilities to branch into such industries. In turn, a region's distance to high-complex activities may be an obstacle to escape such a low complexity trap. The findings in our paper raise doubts to what extent the current setting of S3 policies is adequate to leverage the knowledge base in regions with a greater distance to high-complex activities.

Secondly, we find a stable, but weak coherence of the industrial portfolio in the cluster types complex regions (cluster 2) and lagging regions (cluster 5). In other words, industries with a location coefficient below 1 remained, on average, rather distant to the economic core. For these regions, it might be primarily relevant to enhance the branching potential by establishing closer connections between industries (location coefficient < 1) and the economic base. In both clusters, this long-term overall disembeddedness could prove to be a significant potential obstacle to upgrade local capabilities, and it might weaken regional economic resilience.

Thirdly, a small number of regions show rather unstable and fragile trajectories (cluster 3). The two mini case studies for this cluster illustrate that a more comprehensive understanding in which ways the coherence and complexity of a region's industrial portfolio changed over time might be helpful for implementing S3 policies. In the city of Worms, both the branching potential and complexity

of its capability base deteriorated. A great number of low complex industries, weakly embedded, offer diversification opportunities (location coefficient < 1). This path is mirrored by moderate economic growth. Yet, following the logic of the policy tool of Balland et al. (2019), a diversification into a very small number of high-complex industries having become more closely connected to the economic core would be beneficial. Our findings, however, suggest that such a strategy could be too risky, as, on average, more complex capabilities deteriorated in the long-run. One option could be to create linkages to other regions, facilitating local diversification into more distant activities (Pinheiro et al. 2022). For the second mini case study, Cloppenburg, the trajectory looks quite different. Although the focus of employment in Cloppenburg has remained in simple activities, coherence in both, less and more complex industries, has improved during the observation period, particularly in those linked to the agricultural economic core. Hence, Cloppenburg could make use of an increased number of diversification opportunities in less and more complex activities across a diverse range of sectors. This trajectory is also linked to stronger economic growth. While the logic of the policy tool of Balland et al. (2019) suggests an orientation toward high-complex activities, our long-term analysis reveals that an additional specialization in less complex industries could be favorable for the region as these activities have become also more closely connected to the agricultural economic core over time.

The findings of this paper point altogether to the need of a more comprehensive information base for local authorities in order to successfully design and implement S3 strategies in their regions. This claim has already been made by various related empirical S3 studies (e.g., Deegan et al. 2021; Marrocu et al. 2023), and we add a particular emphasis on a long-term perspective to this call. As a complement to the tool of Balland et al. (2019), we show that information for policymakers on past development trajectories provide important insights for being better able to implement appropriate S3 policies.

Nevertheless, our study is subject to certain limitations. Despite conducting various robustness checks in building sequence clusters and employing different thresholds for defining sequence states, there remains an inherent degree of subjectivity in many of the empirical decisions. Yet, this level of subjectivity is typical for such studies and should be regarded when interpreting the results. Another limitation pertains to the “fragile regions” cluster. While this category captures a variety of unique regional trajectories, it is a residual category, encompassing all sequences not aligning with the stable clusters. Lastly, our study faces several common challenges associated with relatedness research (see Bathelt and Storper 2023). The concept of related variety was recently criticized, particularly for lagging regions, because evidence suggests that these regions might benefit more from unrelated variety (Castaldi et al. 2015; Cortinovis and van Oort 2015), challenging the one-size-fits-all approach of related diversification in S3 and its applicability in less-developed areas. Despite these critiques, relatedness continues to be a fundamental principle of S3, highlighting the need to assess its actual implementation in policy design (D’Adda et al. 2020). Another significant limitation in this context is our focus on endogenous potentials for regional diversification, as

this approach tends to overlook extra-regional linkages and institutional factors that also play a role in shaping regional diversification (Frenken et al. 2023).

Taken together, innovation policy instruments are required to be more sensitive to long-term nature of regional development in general and diversification trajectories more specifically. Data on historical development trajectories are therefore crucial to enable better-informed decisions of national and regional authorities for the implementation of S3 policies. While closer connections between industries in regions with low complexity seem per se advantageous to strengthen their economic base and branching potential, development strategies following the logic of unrelated variety—contradicting prevailing S3 rationales—seem particularly helpful for lagging regions to escape from low complexity traps. Thus, regions should not always strive for complex economic activities, but are also encouraged to diversify into less complex industries, especially those linked to traditional economic cores, in order to increase resilience.

Future research directions should extend our analysis to encompass the entire EU, capturing the increased regional heterogeneity and potentially identifying a wider array of cluster types. Furthermore, an important avenue for research involves connecting our results to the actual S3 policy implementation in various regions (Deegan et al. 2021). Such research could provide valuable insights for policymakers, helping to refine and tailor S3 strategies to the unique economic contexts of different European regions.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s00168-025-01375-5>.

Funding Open Access funding enabled and organized by Projekt DEAL.

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