

Hertrich, Tobias Johannes; Brenner, Thomas

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ORIGINAL ARTICLE



Classification of regions according to the dominant innovation barriers: The characteristics and stability of region types in Germany

Tobias Johannes Hertrich | Thomas Brenner

Department of Economic Geography and
Location Research, Philipps-Universität
Marburg, Marburg, Germany

Correspondence

Tobias Johannes Hertrich, Department of
Economic Geography and Location Research,
Philipps-Universität Marburg,
Deutschhaustraße 10, 35032 Marburg,
Germany.
Email: tobias.hertrich@geo.uni-marburg.de

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Abstract

Lagging regions differ in their characteristics, implying a need for tailor-made policy measures to improve the economic situation in these regions. However, while there are differences between these regions, certain types of regions might exist that share the same obstacles to innovations, allowing for taking similar political measures. This paper examines whether such types of regions can be identified in Germany, what characteristics they possess, and how they change. For this purpose, regional characteristics that are related to innovation barriers are identified and operationalized. Then, a cluster analysis is conducted for the German labor market area. While the identified types of regions are in some way or another also discussed in the literature, the paper provides for the first time a classification within one empirical framework and allows for the study of the dynamics of the types of regions as well as the dynamics within each region inside this framework. The correspondence with the existing knowledge about German regions confirms that it is possible to do such a classification using quantitative data. Furthermore, the stability of the types of regions confirms that such a classification can be considered a good basis for policy measures. The results

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also depict trends that might lead to problems in the future and require policy attention.

KEYWORDS

classification of regions, cluster analysis, innovation barriers, lagging regions

1 | INTRODUCTION

The difference between lagging regions and economically successful regions has been a predominant problem in Germany and most other countries. Despite the good economic situation in recent years, economic differences between strong and weak municipalities are still growing in Germany (Boettcher et al., 2019). Under Section 2(2) (1) of the Spatial Planning Act, policy in Germany is required, *inter alia*, to ensure balanced social and economic conditions. Therefore, policies aim to counteract the inequality through many different programs and measures.

Most economically lagging regions are characterized by comparatively high unemployment, low income, and low economic growth (Brown et al., 2017; Farole et al., 2018). Furthermore, innovation often takes place in large and economically advanced areas, less so in underdeveloped or lagging regions (Bettencourt et al., 2007; Breau et al., 2014; Crescenzi et al., 2012; Feldman & Florida, 1994). Some studies show a correlation between regional structural weakness or economic growth and low innovation activity (Fritsch & Mueller, 2004; Koschatzky, 2018). A high level of innovation activity is one way of improving the economic structure of a region and achieving a more dynamic economy (Brenner & Pudelko, 2019; Ulrich et al., 2007). Therefore, the fostering of innovation activity can and should be a significant component of regional policy and structural support, although not the only one.

However, lagging regions differ strongly in their characteristics, and hence also in the factors that cause the low innovation activities. The concept of territorial capital underlines the different endowments and the respective specificity of each (lagging) region but does not focus on innovation (Morretta, 2021). A large number of existing case studies depict these differences of lagging regions (Boltho et al., 2018; Doloreux & Dionne, 2008; Ejdemo & Örtqvist, 2021; Polese & Shearmur, 2006; Rodríguez-Pose & Wilkie, 2019; Terluin, 2003), which are often caused by historical developments and political decisions, and in particular limited access to resources and networks, less innovative industries, worse finance conditions, and a shortage of specialized labor. Furthermore, different spatial circumstances create different dynamics in such regions (e.g., shown for migration in the case of rural regions close to metropolitan areas compared with peripheral regions by Meister et al., 2023).

In principle, the fundamental differences between the lagging regions in Germany are well known (Küpper & Peters, 2019). Many existing classifications refer to labor market characteristics (Blien et al., 2010; Blien & Hirschenauer, 2018), to settlement structure (of rural regions) (Küpper & Milbert, 2020), to economic and research indicators (Koschatzky & Kroll, 2019), or to some selected socioeconomic parameters (European Commission, 2017; Küpper & Peters, 2019), but a classification of regions on the basis of data on the various characteristics that are connected to innovation processes does not exist so far. Such a classification provides three things: (1) It might provide further insights in additional differences between regions that are detected in case studies that consider one or a few regions, (2) it allows for the identification of general trends in the development of each of the class of lagging regions, and (3) it allows for the comparison of each region's development to the development of its class to understand which developments are usual for this kind of region and to examine in which aspects a region deviates from the general development of its kind. This provides information on policy measures for different types of lagging regions and how they might have to adapt in the future. The ability to compare regions with others of their kind improves the assessment of the impact of policies.



To develop a classification of lagging regions with respect to their innovation problems, the relevant regional characteristics have to be identified. The literature provides an extensive analysis of the various innovation barriers (Coad et al., 2016; D'Este et al., 2011; Hadjimanolis, 2003; McAdam et al., 2004), but innovation barriers are usually examined on the level of firms. Therefore, the connection between innovation barriers and the characteristics of (lagging) regions is rarely examined. However, there are a few studies that examine main barriers to innovation (for small and medium-sized enterprises [SMEs]) at the spatial level of low-income regions, identifying human capital and know-how, infrastructure, access to resources, and entrepreneurial quality as important barriers (Fernández-Serrano et al., 2019; Fernández-Serrano & Romero, 2012; Tödtling & Kaufmann, 2001). Regional aspects are more frequently studied from a system perspective in the literature on regional innovation systems (RIS) (Arnold et al., 2014; Asheim et al., 2019; Asheim & Gertler, 2011; Autio, 1998; Cooke, 1992, 1996; Cooke, 2009; Morgan & Cooke, 1994). This literature also examines some shortcomings of RIS, namely, institutional thinness, fragmentation, and lock-ins, as typical regional barriers to innovation (Martin & Trippl, 2014; Tödtling & Trippl, 2005).

We extend this literature in the following two ways: First, we connect literature on regional innovation barriers and the more firm-oriented literature on barriers of innovations that so far have been unconnected. This provides a better understanding of how regional characteristics cause reduced innovation activities. Second, we examine whether a classification of lagging regions on the basis of quantitative data is possible and helpful to identify type-specific trends and region-specific developments. The available knowledge on German regions allows for the evaluation of the adequateness of such a data-driven classification. Proving the possibility of such a data-based classification builds the basis for applications in other countries, the development of type-specific policy measures, and the evaluation of policy effects considering type-specific developments.

We believe that lagging regions differ in their characteristics and the relevant barriers to innovation. This is supported by the literature arguing for tailor-made policy activities designed for each region separately (Brenner & Niebuhr, 2021). Such region-specific policy measures are antipodal to general region-independent measures. The question that we also aim to answer is whether an approach between these polar approaches is possible. We intend to provide a basis for formulating a policy measure that can be applied to many regions with similar characteristics. Such an approach needs to be systemic by combining various policy measures and requires the existence of regions with similar characteristics. In more detail, it requires regions that face the same combination of innovation barriers so that the same bundle of measures can serve the regions adequately. This paper examines whether such types of regions that face specific sets of innovation barriers exist in Germany.

In this paper, we classify German regions using characteristics that are connected to innovation barriers and examine the identified types and their stability. So far, such an analysis has not been conducted. With the help of cluster analyses, six types of regions were identified. These six types of lagging regions are relatively stable over time and differ in terms of their characteristics and barriers to innovation studied. At the same time, regions frequently change cluster affiliation over the study period. These changes provide relevant information on the dynamics of lagging regions. For the study period, we find that many lagging regions are less affected by the increasing shortage of skilled workers due to the low need for such workers. Furthermore, we find deterioration of founding activity in many regions, especially in the urban hinterland.

The remainder of the paper proceeds as follows: in the second section, RIS (Section 2.1) and research on barriers to innovation (section 2.2) are linked and transferred to the regional level. In Section 2.4, a region classification based on innovation barriers is theoretically derived using the company- and region-specific characteristics described in Section 2.3. On this basis, a cluster analysis is conducted. Section 3 then describes the methodological procedure of the cluster analysis, and Section 4 discusses the results. This section contains the correlations between the properties (Section 4.1), the identified (number of) clusters based on silhouette plots (Section 4.2), the properties of the found clusters (Section 4.3), the change of clusters over time (Section 4.4), and the change of cluster membership of regions in the study period (Section 4.5). Finally, Section 5 concludes.



2 | THEORETICAL BACKGROUND

So far, no theory of regional innovation problems exists, on which we could base our analysis. However, several definitions, concepts, and classifications exist that can be used as a basis for the decisions related to our approach. Two strands of literature are especially relevant: the concept of RIS and the more firm-oriented literature on barriers to innovations. The literature on RIS is more concerned with factors that enhance the innovation capability of regions, although a few studies also examine regional characteristics that cause regions to be less innovative. The innovation barrier literature focuses on factors that hinder innovation processes and success. One could argue that there is a connection between factors that foster innovation activities and factors that hinder them: the lack of innovation-enhancing factors is a barrier of innovation. However, there is only a simple inverse relationship between innovation-enhancing and hindering if the impact of a factor can be added up with the impact of others. The situation becomes more complex if a certain presence of a factor is necessary for innovations to happen, implying a strongly nonlinear relationship. While the former is usually assumed in mathematical approaches, we believe that in reality, the relationships are more complex. Therefore, we believe that it is interesting and helpful to develop a more barrier-oriented perspective in the RIS literature. We contribute to this in Section 2.4. However, some papers in the field of RIS have already taken such a barrier-oriented perspective. Therefore, Section 2.1 only shortly introduces the concept of RIS and mainly focuses on the barrier-oriented discussion in this field. The more firm-oriented literature on barriers to innovations is introduced in Section 2.2 with a focus on the various identified barriers. Our contribution to the theoretical literature is the transfer of these barriers to the regional level (Section 2.3) and the use of the transferred barriers for broadening the barrier-oriented view on RIS (Section 2.4).

2.1 | RIS

RIS are understood as the region-specific, socio-institutional, and culturally embedded setting of all private and public organizations and institutions that are involved in innovation processes (Cooke, 1992). The three core elements are actors, networks, and institutions. Actors are companies, universities and research institutions, public institutions, investors, and venture capitalists, as well as various other organizations and individuals involved in innovation processes. Moulaert and Hamdouch (2006) distinguish between the three important actor groups: companies with high innovation potential (e.g., suppliers, costumers, competitors), local/regional actors (e.g., governments, universities, research institutions, nongovernmental organizations [NGOs], and associations) and innovation intermediaries (e.g., cluster organizations, innovation centers, or technology transfer offices). Companies with high innovation potential often have access to specialized knowledge and resources and can support the growth of the RIS through research and development (R&D). Their goals are to develop new products, processes, or services to gain a competitive advantage, enter new markets, and generate growth. Local and regional actors have an important role in creating an innovation-friendly environment within the RIS. Universities and research institutions can provide knowledge and expertise and initiate innovative projects. Governments can promote/encourage R&D activities and provide infrastructure (e.g., faster Internet connection or connectivity) through their funding policies and improve the RIS innovation output. Their goal is to promote innovation activity in the RIS, job creation, and growth in the region. Innovation intermediaries can act as “bridges” between enterprises and to other actors in the RIS (e.g., research institutions). They are committed to the transfer of knowledge and resources between the actors in the RIS. Their goals are to facilitate the exchange of knowledge and resources, promote cooperation between the actors in the RIS, and support enterprises in the development and implementation of innovation projects (Moulaert & Hamdouch, 2006). These networks between the aforementioned actors generate knowledge transfer and joint learning, which is often the way of interacting. The sociocultural embedded institutional setting of networks, regulations, informal norms, and beliefs are considered crucial for the innovation process to take place in a region (Isaksen et al., 2018; Scott, 2008).



The theoretically derived concept has been statistically examined in many studies. For example, studies of R&D expenditures show that the innovativeness of the RIS depends significantly on existing firms and their innovation efforts (e.g., Czarnitzki et al., 2009) or the larger number of companies in a particular industry (Fritsch & Slavtchev, 2011). In addition, a positive influence of existing universities and research institutions (e.g., Anselin et al., 1997), population density (Broekel et al., 2015), foreign direct investment (FDI) (Li et al., 2020), human capital (Charlot et al., 2015), social capital (Hauser et al., 2007), gross domestic product (GDP), and local market size (Li et al., 2020) is found.

While the literature on RIS generally focuses on factors that support innovation processes, some also define circumstances that hinder innovation processes, which is the more relevant part considering the context of this paper. Tödtling and Tripl (2005) identify three aspects that hinder innovation from a system perspective: organizational thinness, negative lock-in, and fragmentation. In organizationally thin RIS, crucial elements of the system are missing or insufficiently developed. Frequent examples of such missing elements are the lack of a critical mass of innovative firms, a low level of clustering, or a weak endowment with key institutions and organizations. Although combinations of RIS shortages are often observed, some system failures are more important than others in specific types of regions. Organizational thinness hinders innovation, especially in peripheral areas (Tripl et al., 2016), which often contain less R&D and innovation activities, SMEs operating in traditional industries, low knowledge uptake from extra-regional sources, and a weak structure of organizations (Doloreux & Dionne, 2008). Complementarily, Zukauskaitė et al. (2017) distinguish further between organizational and institutional thinness/thickness. Under organizational thinness, Zukauskaitė et al. (2017) understand the missing of a critical mass of companies, research and scientific institutions, organizations, and associations. Institutional thinness, meanwhile, is understood as the lack of formal (e.g., written law and rules) and informal (e.g., informal cooperation culture and mindset) institutions.

RIS with a negative lock-in show an 'over-embeddedness and over-specialization in mature sectors and outdated technologies' (Tripl et al., 2016, p. 27). These regions contain strong spatial concentrations of capital-intensive industries (e.g., steel, coal mining). Therefore, RIS with negative regional lock-ins occur often in old industrial areas that suffer from de-industrialization (Hassink, 2010; Tödtling & Tripl, 2005). Grabher (1994) differentiates between functional, cognitive, and political lock-ins. Functional lock-ins are characterized by a hierarchical and close interfirm relationship that hinders the firm's development of boundary-spanning functions (e.g., their own R&D). Firms that struggle with a cognitive lock-in have a mindset that hinders them in recognizing secular trends and technological developments. A political lock-in is an institutional setup that preserves existing traditional industrial structures, thus unnecessarily slowing down industrial restructuring and indirectly hindering the development of regional potential (Hassink, 2010).

Fragmented RIS are RIS with insufficient interaction between the elements. This lack of connectivity and networking leads to reduced or inexistent knowledge exchange and weak or insufficient interactive learning between the actors. Fragmented RIS often hinders innovations in metropolitan areas with, in principle, well-equipped actors (Martin & Tripl, 2014; Tödtling & Tripl, 2005; Tripl et al., 2016).

The aforementioned actors not only experience the innovation barriers described by Tödtling and Tripl (2005), but it also becomes clear, through the systemic perspective, that actors can be and usually are both source and sufferer of barriers to innovation. In other words, through their small numbers (organizational thinness) and/or through their actions (or inactions), actors can be external barriers to innovation for other actors from a systemic perspective. Some barriers within the system probably result from the fact that the respective actors do not always pursue the same goals (Moulaert & Hamdouch, 2006). Some studies imply, in a very simplified way, that researchers at a knowledge institution often have the (rather theoretical) goal of publication and not necessarily the economic exploitation of the research results (van Looy et al., 2006). Moulaert and Hamdouch (2006) give the example that companies with high innovation potential might close themselves off to cooperation with other actors in RIS and instead try to protect their own innovations and competitive advantages. This (sometimes) different orientation of actors and the interdependencies and conditions within a system highlight the importance of the third group of actors: the



intermediaries, governance structures, innovation clusters, innovation policies, and managers in coordination and cooperation with different actors in a RIS (fragmentation) (Fritsch & Slavtchev, 2011).

2.2 | Firm-level innovation barriers

While research on RIS has identified important problems of a systemic nature, there are also many obstacles to innovation that unfold on the company level, which are the main generators of innovations. Companies are confronted with several challenges in the innovation process, which in the literature are called innovation barriers (e.g., D'Este et al., 2011, 2008; Galia & Legros, 2004; Hadfield, 2008; Hadjimanolis, 2003; Iammarino et al., 2009; Piatier, 1984). Although barriers to innovation occur regularly, companies often pay too little attention to them (Storey, 2000). Many barriers are not properly addressed before they occur in the company and consequently impact innovation. From a short-term perspective, barriers in the innovation process lead to innovation change, delay, or complete prevention of innovation. In the long term, barriers and the innovation projects that are not realized lead to profit and productivity losses and possibly to a loss of value for the company (Coad et al., 2016; Mirow, 2010). Furthermore, it is the case that more innovative companies face innovation barriers more often (Baldwin & Lin, 2002; Iammarino et al., 2009).

Barriers to innovation can be structured in different ways. For example, Mirow et al. (2007) argue for a division of barriers into symptom and cause. Schültz (2014) sees an interplay of three areas: technical/content, organizational, and social complexity. Other authors structure barriers on the basis of their occurrence in the phase in the innovation process (e.g., Hauschildt & Salomo, 2012). Additionally, D'Este et al. (2011) divide innovation barriers into two types: revealed barriers and deterring barriers.

Often, the different barriers to innovation are divided according to their origin into barriers external to the firm (also exogenous) and barriers internal to the firm (also endogenous) (Goepel, 2014; Hadjimanolis, 2003; Piatier, 1984). External barriers can only be influenced marginally by the company and arise in the environment and surroundings of the company. Internal barriers arise within the firm and are therefore easier for the firm to change (Hadjimanolis, 2003). To connect innovation barriers to region types such a classification is helpful. We use the classification by Hadjimanolis (2003) into external (market-related, government-related, other) and internal (people-related, structure-related, and strategy-related) barriers and complemented it by distinguishing further sub-categories using insights from the literature. The result is presented in Table 1.

The different company-internal barriers are often interrelated. Strategic and management-based barriers, for example, are anchored at the top management level of the company and concern the strategic orientation of the company. However, an orientation of the company that hinders innovation or inadequate strategic objectives at the highest management level often leads to structural barriers, such as insufficient human capital or a lack of financial R&D resources in the company. These problems often cause an innovation-inhibiting (and often sluggish) company structure with long information and decision-making paths (D'Este et al., 2011; Hadjimanolis, 2003; Mirow, 2010). The individual employees of the company act within a given framework and according to the instructions of the management so that they are also influenced by the fundamental orientation of the company and structural barriers. At the individual employee level, knowledge and willpower barriers (Hauschildt & Salomo, 2012) are the most important barriers to innovation.

Barriers to innovation that are external to the company originate in the company's environment, implying some concordance with the insights from RIS research. External barriers can only be insufficiently influenced by the company itself (Hadjimanolis, 2003). Firms often face certain market and industry constraints that can act as barriers to innovation (Pellegrino & Savona, 2017; Tang & Yeo, 2003). Political institutions set important standards, rules, norms, and frameworks, covering almost all areas of entrepreneurial activity. Such regulations and standards are often restrictive and can act as barriers to innovation (Palmer et al., 1995). The influence of such regulations on a firm's innovativeness is relatively small (Cooper, 1975) and depends additionally on the market situation (Blind et al., 2017;



TABLE 1 Overview of internal and external barriers to innovation (modified illustration based on Hadjimanolis (2003)).

Internal barriers		External barriers	
Group	Barriers (B)	Group	Barriers (B)
I. Strategic and management-based barriers	B1. Leadership shortcomings in management	IV. Market and industry barriers	B15. Shortage of skilled workers (within the branch)
	B2. Lack of risk-taking and commitment		B16. Barriers to market entry
	B3. Company goals and/or strategy are missing, unclear, or hinder innovation		B17. Market uncertainty/lack of information
	B4. Conflicts of interest and priority		B18. High return target (especially for PLC)
	B5. Poor marketing and sales management		B19. Capital market access restrictions
II. Structural barriers	B6. Lack of resources and information (e.g., human capital deficiencies)	V. Regulatory institutional barriers	B20. Standards, regulations, and laws
	B7. Poor organizational structure and organizational inertia		B21. Bureaucracy and bad/slow communication channels and procedures
	B8. Lack of process relevance of innovations		B22. Barriers to trade and tax systems
	B9. Insufficient internal cooperation and information flow		B23. Legal uncertainty
	B10. Unclear or too little decision-making authority		B24. Lack of support from political institutions for business and innovation
	B11. Corporate and learning culture that inhibits innovation		B25. More difficult access to intellectual property rights
III. Individual barriers (employee level)	B12. Barriers to motivation	VI. Social barriers	B26. Political power and interest conflicts
	B13. Barriers to competence		B27. Climate hostile to innovation (e.g., skeptical attitude toward socioeconomic change)
	B14. Capacity problems (time)		B28. Static school and education system
		VII. Barriers to Cooperation	B29. Lack of entrepreneurial spirit in society
			B30. Resistance to external ideas ('not invented here')
			B31. Too few external connections and knowledge transfer
			a. Lack of cooperation with other companies (vertical, horizontal, and diagonal)
		IX. Public infrastructure barriers	b. Insufficient cooperation with institutions (universities, research institutes, and intermediaries)
			B32. Lack of trust and prejudices
			B33. Lack of transport infrastructure
			B34. Lack of digital infrastructure
			B35. Lack of support infrastructure (including intermediaries)



Sainio et al., 2012). The education and training system play an important role in providing innovative employees to firms. If society tends to be skeptical to socioeconomic change and science and is strongly status quo afflicted, then these might represent societal barriers to innovation (Büttner et al., 2004; Hadjimanolis, 2003; Tang & Yeo, 2003). Barriers to cooperation arise primarily when companies do not cooperate or cooperate insufficiently with other actors for various reasons (e.g., resistance to external ideas, lack of adequate [nearby] partners, lack of trust, and prejudice) (Lewandowska & Danik, 2016). As a consequence, innovation is hindered or even prevented. This applies to horizontal and vertical cooperation as well as to all other forms of cooperation (Hadjimanolis, 2003). Cooperation is also seen as one way to overcome obstacles to innovation (Antonioni et al., 2017; Faria et al. 2010). Public infrastructure can also hinder innovation; for example, inadequate or aging road infrastructure can hinder/slow down the transport of goods and increase costs for businesses that rely on the efficient transport of goods (Agrawal et al., 2017; Glaeser & Poterba, 2021; Yang et al., 2021). A lack of digital infrastructure can limit access to digital services, make cooperation more difficult, and thus affect the potential for innovation and development (Greenstein, 2021; Ilgmann, 2019; Lee et al., 2015; Saleminck et al., 2017). As already described in Section 2.1, the lack of government assistance such as funding, transfer managers, or cluster managers can also be detrimental to innovation (Moulaert & Hamdouch, 2006).

Table 1, which is based on research from Hadjimanolis (2003), contains many internal and external barriers to innovation that are collected from various studies and surveys. We added all barriers that we found in the literature so that we are quite confident that Table 1 contains the most relevant and especially the most important barriers. Nevertheless, the completeness of this list cannot be guaranteed.

2.3 | Regional and enterprise characteristics

Some of the innovation barriers can be related to the regional level. Nevertheless, besides the previously mentioned literature on RIS, the connection between regional characteristics and innovation barriers is rarely mentioned in the literature on the innovation barriers. Therefore, we will develop a comprehensive and structured link between regional characteristics and the various innovation barriers in this paper.

The occurrence and importance of barriers to innovation are often linked to the size of the company (Piatier, 1984; Rosa & Mohnen, 2000). Companies that do not innovate (or are less innovative) are on average smaller (have fewer employees) than innovative firms (D'Este et al., 2011; Romero & Martínez-Román, 2012). Large firms are expected to face more internal (e.g., B1; B2; B7; B9; and B10 in Table 1) than external barriers to innovation compared with SMEs. Because of the mentioned internal barriers, larger firms are, compared with SMEs, less adaptable and agile with regard to external barriers, although they theoretically have the advantage of possessing the expertise and resources to overcome these external barriers (Romero & Martínez-Román, 2012; Vossen, 1998). On the one hand, small firms have some advantages when it comes to some internal barriers (e.g., simpler structures, direct communication channels, more flexible and adaptable) (Dean et al., 1998; Fernández-Serrano & Romero, 2012). On the other hand, SMEs suffer from other internal barriers (lack of skilled workers and financial resources, management quality) (Coad et al., 2016; Fernández-Serrano & Romero, 2012; Hadjimanolis, 1999; Piatier, 1984).

It is expected that SMEs and young firms are, compared with large enterprises, more affected by both internal and external financial barriers (B6b and B19 in Table 1) (Arza & López, 2021; Coad et al., 2016; Hadjimanolis, 1999; Mohnen et al., 2008). Arza and López (2021) highlight that cost obstacles in particular deter SMEs more from investing than they do large companies. Access to bank capital and venture capital or investors is more difficult for SMEs than for older and larger firms as well as firms belonging to a company group (Mohnen et al., 2008; Storey, 2000; Tiwari et al., 2008). Ylinenpää (1998) states that within a cohort of SMEs, 'micro-firms' suffer most from insufficient venture capital. Savignac (2008) examines differences between individual sectors. Accordingly, firms in the electrical and electronic equipment sector suffer disproportionately from financial barriers. The riskier



and newer an industry or sector is, the more it struggles with financial barriers (Canepa & Stoneman, 2002). Additionally, Engel (2002) observes that in Germany, high-density regions benefit more from venture capital activities. These high-density regions tend to be regions with a high 'technological potential' (Engel, 2002, p. 17) in the form of a strong presence of non-university, university, and industrial R&D facilities. In rural regions, it is rare to find companies (especially in the software sector) with venture capital (VC) funding. Significantly less venture capital also flows into structurally weak regions. These dependencies of innovation barriers on the size of firms imply regional issues if regions are dominated by smaller or larger firms, causing the respective innovation barriers to be more prevalent in these regions.

Furthermore, SMEs have disadvantages compared with larger companies in employing skilled workers (B6 and B15 in Table 1) due to lack of time (B6a in Table 1) (Hadjimanolis, 1999; Piatier, 1984). In addition, Strobel and Kratzer (2017) find that the internal barriers, lack of expertise, and capacity overload are main obstacles to innovation for SMEs. Small firms typically cannot offer their employees as attractive wage terms, job security, education, training, and career opportunities as larger firms. Training suitable skilled employees also often requires greater effort for small firms (Hadjimanolis, 1999). Coad et al. (2016) find that the lack of qualified workers can hinder a high productivity. Furthermore, they find that exporting firms struggle less with the lack of qualified workers, financial barriers, and regulatory barriers. In peripheral regions, external innovation infrastructure is often less developed than in central regions. This is particularly evident in the decreased availability of skilled labor and know-how (Anderson et al., 2001). Nerlinger (1998) highlights that for young high-tech companies, the availability of skilled labor and regional know-how are the most significant location factors, along with proximity to customers. Peripheral regions may thus even be considered 'hostile environments' for new, small, and innovative firms (Anderson et al., 2001). Tödtling and Kaufmann (2001) conclude that SMEs are fewer involved in innovation networks than large companies. Major and Cordey-Hayes (2003) examine that SMEs in particular have a lower propensity to interact and cooperate with other players in the region such as universities (B6; B30; and B31 in Table 1). The authors attribute this to a lack of time, management, knowledge resources, and experience. From a regional perspective, spatial proximity favors informal collaboration, human capital formation, and business spin-offs. Most R&D institutions are located in large agglomerations, exhibiting greater clustering, variety, and commercialization of new knowledge. As a result, cooperation takes place predominantly within or between these agglomerations (Bathelt & Glückler, 2018; Engel, 2002).

In the case of SMEs, it is primarily up to the company owner(s) to perceive market signals, information, and innovation opportunities. Therefore, the characteristics and education level of the entrepreneur are very important (Romero & Martínez-Román, 2012; Vossen, 1998). The results from Romero and Martínez-Román (2012) show that small enterprises run by self-employed entrepreneurs exhibit higher levels of innovative behavior than those run by non-self-employed managers. SMEs are also significantly more affected by market uncertainty and ignorance (B17 in Table 1). At the same time, they can often afford to spend fewer resources on R&D compared with large firms, and due to the market power of large firms they also often have more difficulties in accessing and entering markets (B16 in Table 1) (Levin, 1978). Moreover, it is more challenging for SMEs to become a part of successful commodity chains and export goods (McAdam et al., 2004). Therefore, small firms' innovation strategies tend to focus on flexibility and market niches (Vossen, 1998). Firms in peripheral regions have poorer market access compared with firms in well-connected, urban areas. Anderson et al. (2001) describe the disadvantages of peripheral areas in terms of limited customer base, larger distances to markets and suppliers, and a limited pool of well-educated workforce. According to Porter (2014), distinctive economies of scale, distinctive product differentiation, high capital requirements at market entry, difficult access to distribution channels, size-independent cost advantages (through, e.g., location advantages or subsidies), and political measures (e.g., tariff barriers) act as causes for a hindered market entry of companies.

Bureaucratic hurdles and lack of support from political institutions particularly affect SMEs (Hadjimanolis, 1999; Strobel & Kratzer, 2017). Political disinterest at the local level is also linked to the lack of relevance, and often presence, of large companies (B24; B21 in Table 1). SMEs also have less influence on technical standards and policy regulations because of their low market power and public presence (Piatier, 1984) (B20 in Table 1). SMEs are also



hindered in their access to property rights (B25 in Table 1). Furthermore, they face greater obstacles in protecting intellectual property and in searching for and applying for patents. According to Hadjimanolis (2003), this is linked with a lack of suitable skilled workers and associated high costs.

Because of differences in regional characteristics and social attitudes, there are regional disparities in the propensity to start a business (B29 in Table 1). Müller and Korsgaard (2018) emphasize the often poorer resource conditions in rural areas compared with urban areas. Bergmann and Volery (2006) find for Switzerland that more startups are created in economically successful regions, which are characterized by a high start-up rate, high purchasing power, self-employment rates, and low unemployment rate. This is likely to be the case for high-quality start-ups. Overall, entrepreneurship in low-income regions can also be very high. In general, a distinction must probably be made between regions with high rates of necessary entrepreneurship (often in lagging regions) and regions with increased casual entrepreneurship (economically well-performing regions) (Acs et al., 2005). Engel (2002) emphasizes the prominent position of the industry as an incubator for innovative start-ups. There are thus regional disadvantages in the probability of start-ups in economically and structurally weak regions (Martin & Tripl, 2014; Tödtling & Tripl, 2005). Entrepreneurs in low-income regions notice human capital and infrastructure as the main barriers to innovation (Fernández-Serrano et al., 2019). There is also a lower entrepreneurial quality from SMEs in low-income regions (Fernández-Serrano & Romero, 2012). Rural areas in particular have a lower level of public infrastructure than urban regions (Ilgmann, 2019; Saleminck et al., 2017).

The dependencies of innovation barriers on the company and regional characteristics are summarized in Table 2. It is shown that SMEs, economically lagging regions, and rural regions are affected the strongest by innovation barriers.

2.4 | Classification of regions based on dominant innovation barriers

This section takes a first theoretical step to classify regions with low innovation activity according to the dominant innovation barriers on the basis of the insights previously documented. Such a classification does not yet exist in the literature. Previous classifications of lagging regions have been based on identifying and measuring structural weakness. As key indicators, the GDP per inhabitant and the unemployment rate are used (BMW, 2016; European Commission, 2017; Koschatzky & Kroll, 2019).

The idea is to enrich the RIS literature by a particular view on regional characteristics that hinder innovative activity. While the description of the RIS in this literature provides a good starting point, most of the works in this field focus on identifying the success factors. An exception is the work by in Tödtling and Tripl (2005), who identify three regional innovation barriers: organizational thinness, negative lock-in, and fragmentation. We use the relationships between innovation barriers, regional characteristics, and company characteristics that are found in literature and described in Section 2.3 to extend this view and understanding on RIS barriers. The innovation system concept allows for the integration of the firm-level innovation barriers because firms and their interaction with other regional actors and circumstances build a central part of the system. The functioning of a RIS is seen as the result of the system's firms, the other present actors, and the interaction of all of them. The former means that firm-internal barriers cause regional barriers if regions are dominated by companies with corresponding characteristics. Of course, this transfer is then based on the majority of firms and does not hold for all individual firms in a region. The firm-external innovation barriers can be directly transferred to the regional level, because they relate either to the missing of other actors in the region or to problems in the interaction with them. Table 3 lists the various regional characteristics and the particularly relevant innovation barriers connected to them and results from viewing the information in Table 2 from a regional perspective.

From this theoretical perspective, we identify six types of regional innovation barriers. R1 and R2 are based on firm characteristics, R3 and R4 are based on regional characteristics, R5 is based on the interaction within the region, and R6 represents a dynamic aspect of the firm population.

**TABLE 2** List of innovation barriers and their dependence on regional and enterprise characteristics.

Barriers to innovation		Enterprise differences	Regional differences
Esp. B1, B2, B5, B7, B9, B10	Internal barriers	Larger companies are more affected	Lower entrepreneurial quality from SMEs in low-income regions
B6b	Lack of internal financial resources	<ul style="list-style-type: none"> • Smaller and young companies are more affected • There are sector differences • Companies that belong to a group of companies are less affected 	
B6, B6a, B15	Lack of skilled workers and time	<ul style="list-style-type: none"> • Smaller companies are more affected because of attractiveness • Firms with higher productivity are more affected • Exporting firms are less affected 	Rural and lagging regions are more affected due to attractiveness (skilled workers)
B6, B30, B31	Insufficient cooperation	<ul style="list-style-type: none"> • SMEs are less often engaged in innovation networks than larger firms 	<ul style="list-style-type: none"> • Lagging regions are more affected due to a lack of partners • Regions without research institutions and universities are more affected due to a lack of partners
B16	Barriers to market entry	<ul style="list-style-type: none"> • Small companies are more affected because of market power • There are sector differences 	Companies in peripheral regions have disadvantages in market access
B17	Market uncertainty and ignorance	Smaller companies are more affected because of resources and market access	
B19	Lack of external financial resources	Smaller companies are more affected due to higher dependence on external funds and poorer access to credit	Rural and lagging regions are more affected by the lack of VC companies
B29	Lack of start-up and foundation activities	There are sector differences	Low firm foundation activities might be caused by many different regional characteristics, such as low economic attractiveness and remote location but also culture and alternative job opportunities
B20; B21; B24	Regulatory institutional barriers	<ul style="list-style-type: none"> • SMEs have less influence on technical standards and regulations • SMEs are more affected by bureaucratic hurdles • SMEs suffer more often from a lack of political support • Exporting firms are less affected 	
B25	More difficult access to intellectual property rights	SMEs are more affected	
B33, B34	Lack of public infrastructure		Rural regions are more affected



TABLE 3 List of regional characteristics, the especially relevant barriers to innovation, and the operationalization used in the empirical approach below.

Region characteristics		Barriers to innovation	Operationalization/variables
R1	SME-dominated economic structure	Lack of financial resources (B6, B19), market access problems (B16, B17), skills shortages (B6c, B15), insufficient cooperation (B6, B30), regulatory barriers (B20, B21, B24)	<ul style="list-style-type: none"> Share of large firms (firms with more than 250 employees); source: INKAR database from the Federal Institute for Research on Building, Urban Affairs, and Spatial Development
R2	Dominance of large weakly innovative companies	Internal barriers (B2, B7, B10, B12)	<ul style="list-style-type: none"> Share of employees with a university degree; source: Institute for Labor Market Research and Employment Research (IAB)
R3	Rural regions	Lack of skilled workers (B6, B15), market access problems (B16), lack of external financial resources (B19), lack of public infrastructure (B33, B34)	<ul style="list-style-type: none"> Spatially weighted population density; source: Statistical Office of Germany (Statistisches Bundesamt) and author calculations based on traveling distances Transport infrastructure: average driving time to next highway, airport, and interregional train station; source: INKAR database
R4	Lagging regions (hardly any activities in dynamic, innovative industries)	Lack of skilled workers (B6, B15), insufficient cooperation (B6, B30), lack of external financial resources (B19), lack of propensity to start a business (B29)	<ul style="list-style-type: none"> GDP; source: INKAR database Structural strength: industry shares according to Brenner and Pudelko (2019); source: IAB Shortage of skilled workers: time to fill qualified job vacancies; source: IAB
R5	Cooperation-weak regions (research-weak regions)	Insufficient cooperation (B6, B30)	<ul style="list-style-type: none"> Number of publications; source: Web of Science (WoS)
R6	Low founding activity	Missing foundation inclination (B29)	<ul style="list-style-type: none"> Number of foundations; source: Centre for European Economic Research (ZEW)

The types of regions also partially match the three types of regional barriers to innovation that were declared in Tödtling and Trippl (2005), namely, organizational thinness, negative lock-in, and fragmentation. The negative lock-in situation matches our case R2 with a dominance of large, weakly innovative firms, especially in the case of functional and cognitive lock-ins. Fragmentation is strongly connected to insufficient cooperation (R5). In the empirical approach, we narrow this down to research-weak regions because spatially inclusive and comprehensive information about the cooperation activity in regions is not available. In connection with innovation barriers, research cooperation is the most crucial part of cooperation activity. There are several reasons for insufficient research cooperation. One reason is the lack of research facilities. This is the only aspect that can be well represented by empirical data. Of course, this does not reflect cooperation activity completely, which we are not able to represent adequately in our approach. As a consequence, the problem of fragmentation is only partly included in our approach. Organizational thinness is related to some of our regional characteristics such as low economic activity (lagging regions) and missing science institutions (research-weak regions). Institutional thinness can be defined as a seventh type of region but is missing in Table 3. We decided against listing this type because it would not follow the same logic that was applied to the other types (deducing it from Table 2), and it also would cause difficulties to operationalize institutions



(Rodríguez-Pose, 2013; Tripl et al., 2016; Zhu et al., 2019). Furthermore, this type can be seen as a combination of some of the types listed in Table 3, namely, R3, R4, and R5.

To sum up, the theoretical perspective provides us with six types of regional innovation barriers. Our argument is that with respect to the underlying regional characteristics, the innovation performance of a region is not simply a sum of these characteristics. Instead, the lack of certain characteristics, or in other words, the presence of certain barriers, leads to a low regional innovation performance independent of other characteristics. However, several of the region properties listed in Table 3 often occur together. For example, rural regions are often also weak in a structural and research sense, and the economic structure is characterized by many small firms. Likewise, many regions in eastern Germany, not only rural regions, are characterized by structural weakness and the absence of large firms. Therefore, the theoretically obtained types of regional innovation barriers might correspond to types of regions, one by one. For this reason, the next step is an empirical investigation of the types of regions and their characteristics in the context of low innovation performance.

3 | EMPIRICAL APPROACH

The empirical analysis aims to classify the German regions concerning characteristics connected to innovation barriers. Therefore, the regional level and the characteristics used must first be determined.

The central variable is the innovativeness of regions (*INNO*). In the literature, the usual measure for this is patents, although it underestimates the innovation activities and comes with a number of biases. The shortcomings of choosing the number of patents as a measure of innovativeness are the following: not all inventions are technically patentable; firms have different inclinations to patent their inventions; non-technological, organizational, and marketing innovations are not captured by patents; and different patent restrictions (costs, time, protection) exist among countries (Archibugi & Pianta, 1996). Therefore, it would be preferable to use alternative innovation measures in addition. The use of R&D expenditures or R&D staff is an option that we considered, but data for the whole studied period are not available. Similarly, measures for the so-called Doing, Using, and Interacting (DUI)-mode innovations (Alhusen et al., 2021) would be a good complement, but data are not available for our set of observations. Better data availability will make an extension of our approach in this direction possible in the future.

Despite the previously mentioned shortcomings, we use patent data that are widely available and can be simply assigned to regions with the help of inventor addresses. If patent registrations were considered exclusively at the company level, they would often be reported exclusively at their main headquarters. Thus, this approach is less representative of the region in which the invention actually took place. Therefore, we decided to use inventor addresses from patent data (patents without a sufficient address, meaning at least the city name, are not considered, which account for less than 10% of the patents). The latter makes labor market areas (LMAs) the adequate regional analysis unit. LMAs are based on the idea that most people work and also live in that region, which fits very well with our analysis. In this respect, the private addresses of inventors often fall into the associated LMA in which the invention took place.

3.1 | Regional characteristics and their operationalization

We previously identified regional characteristics that are connected to innovation barriers, and thus, lead to lower innovation activities. The operationalizations are listed in Table 3 and are discussed in the following paragraphs.

According to the previously mentioned arguments, SME-dominated economic structures (R1) as well as large sluggish companies (R2) can lead to lower innovation activity. Hence, both regions with many small firms and regions with many large firms might be more innovative. The empirical data show that, on average, regions with predominantly large firms are more innovative. The disadvantage of lagging (financial) means in the innovation process seems



to be a more determining barrier than the various internal barriers in large firms. Therefore, we use as a measure for both arguments, namely, the share of large firms (more than 250 employees) in a region (*LARGE*), which reflects the lack of powerful actors. These data are available from 2006 till 2015 (INKAR database).

To reflect the sluggishness of (large) companies, we use the share of all employees in a region that have graduated (*QUAL*). The assumption behind this is that firms with a lower rate of highly qualified employees are, in general, less innovative. The data are obtained from the Institute for Employment Research (IAB) for the years 2002 until 2019.

Rural regions (R3) are operationalized by population density. One approach is to use the population density, which is calculated for each LMA by dividing the population by area. However, this is only part of the story since the previous arguments are also related to the distance to agglomerations or the belonging to metropolitan areas. Therefore, we use the spatially weighted average of the population density (*spDENS*). For each municipality i , a weighted average of the population density of all surrounding municipalities is calculated using the following distance decay function (see Brenner, 2017):

$$spDENS_i = \sum (w_{ij} \cdot DENS_j)$$

$$w_{ij} = \frac{1}{1 + \left(\frac{d_{ij}}{r}\right)^{-s}},$$

where w_{ij} is the used weights, d_{ij} denotes the driving time from municipality i to municipality j (based on the street map from the year 2012), and r and s are parameters determining the exact shape of the decay function (Brenner, 2017), which are set to $r = 45$ min and $s = 7$ here (as used and discussed in Brenner & Pudelko, 2019). The value for each labor market area is calculated as the weighted average of the *spDENS_i* of all contained municipalities weighted by the number of their inhabitants. By applying this procedure, rural areas near big cities obtain higher values than rural areas in the periphery. The data cover official inhabitant numbers for all years from 2002 till 2019.

As a second measure for the remoteness of the regions (R3), we use the driving time to the next highway, the next airport, and the next interregional train station (with IC/ICE trains). To condense the number of variables, we build the average of these three driving times for each labor market area (*TRANS*). The data are only available for the year 2012 (INKAR database).

To operationalize lagging regions (R4), three variables are used: GDP, structural strength, and skill shortage. First, to represent the economic activity in the regions, we use the GDP of each region (*GDP*). These data are available from 2002 until 2017 (INKAR database). Second, besides having a low overall economic activity, lagging regions also have a disadvantageous industry structure. We use the measure of structural strength developed by Brenner and Pudelko (2019). This measure assigns a value to each industry on the basis of its employment dynamics, qualification, and innovativeness and calculates its weighted average for each region on the basis of the industries' shares in the region (*STRUCT*). The data necessary for the calculation of the share of industries have been obtained from the IAB for the years 2007 until 2019. Third, lagging regions also have issues attracting skilled workers. However, this also holds true for rural regions. Hence, the measure for skill shortage (*SKILL*) can be seen as a characteristic of economically lagging as well as rural regions. In this paper, it is measured by the average time (in days) to fill a qualified position (qualification level 2 and higher in the IAB classification, containing workers with at least 2–3 years of job qualification). To obtain a measure that is positively related to innovativeness, we use the negative value of the average vacancy duration. The data were obtained from the IAB for the years 2007 until 2019.

To operationalize research-weak regions (R5), we use the number of paper publications (*SCIENC*). This aims to represent the presence of scientific activity in the region that might support the innovation activity of firms in the region. The data are taken from the Web of Science with all author addresses assigned to the LMA and fractional counting. The data are available for the years 2002 until 2019.



Finally, regions with a lack of start-up activity (R_6) are identified with the help of the number of firm foundations in the region (*FOUND*). The data have been obtained from the Leibniz Centre for European Economic Research (ZEW) for 3-year periods from 2002 until 2019. Table 4 gives a brief overview of the variables and data used.

3.2 | Statistical approach

As previously argued, we believe that certain regional characteristics work as an innovation barrier independent of other local factors. This aspect cannot be captured in a simple mathematical model and cannot be analyzed by a

TABLE 4 Description, data source, and years of data availability of the used variables.

Variable shortcut		Variable	Description	Data source	Years of data availability
INNO		Innovativeness	The number of registered patents per inhabitant Use of inventor addresses from patents	PATSTAT database	2002–2019 (yearly)
SCIENC		Scientific research	Number of journal paper publications per inhabitant	Web of Science database	2002–2019 (yearly)
URBAN	spDENS	Population density	Spatially weighted population density	Statistical Office of Germany (Statistisches Bundesamt) and own calculations	2002–2019 (yearly)
	TRANS	Transport infrastructure	Average driving time to next highway, airport, and interregional train station	INKAR database	2012
QUAL		Qualified employees	Share of employees with a university degree	Institute for Labor Market Research and Occupational Research (IAB)	2002–2019 (yearly)
ECON	STRUCT	Industrial structure	Industry shares according to Brenner and Pudelko (2019)	Institute for Labor Market Research and Occupational Research (IAB)	2007–2019 (yearly)
	GDP	Economic strength	GDP per inhabitant	INKAR database	2002–2017 (yearly)
LARGE		Large firms	Share of large firms (firms with more than 250 employees)	INKAR database	2006–2015 (yearly)
FOUND		Firm foundations	Number of foundations per inhabitant	Leibniz Centre for European Economic Research (ZEW)	2002–2019 (for 3-years periods)
SKILL		Skilled labor availability	Time to fill qualified job vacancies	Institute for Labor Market Research and Occupational Research (IAB)	2007–2019 (yearly)



regression approach. Furthermore, due to the structure of regions, several regional characteristics that might constitute such an innovation barrier occur together. Hence, it is impossible to detect the regional characteristics that are responsible for the low innovativeness by a statistical approach. Instead, we classify the German regions according to the various characteristics previously identified as being potential barriers and their innovativeness. This allows us to check whether the types of regions that we derived theoretically exist in reality and whether they are connected to low innovation activity. Hence, the main part of our approach is a cluster analysis. To reduce the number of variables for the cluster analysis, we conduct a correlation analysis before and merge highly correlated variables.

We use a simple k-means clustering based on Euclidean distances and the Hartigan–Wong algorithm (Hartigan & Wong, 1979). The number of clusters k is determined by a silhouette analysis (Rousseeuw, 1987). To prepare the data for the cluster analysis, the usual standardizing approach is applied (Romesburg, 2004). This includes subtracting from each value the average value of this variable and dividing the result by the variables' standard deviation. We apply this procedure separately for each of the periods given in the following paragraph. This implies two characteristics of our data. First, time trends that apply to all German regions are eliminated. Second, all values are distributed around zero with positive values signifying above average characteristics.

The data are available on a yearly basis, covering a long period (most variables from 2002 till 2019). Due to fluctuations, it is not adequate to use data for each year separately. Furthermore, some variables are not available for the whole period. At the same time, one of our aims is to check whether the profiles of regions remain stable over time. Therefore, we build three periods: 2002–2007, 2008–2013, and 2014–2019. For each variable, the average of all available values is assessed for each period. For all variables except transport infrastructure, at least one value is available in each period. In the case of transport infrastructure, only values for the year 2012 are available. Assuming that transport infrastructure does not change much, we use this value for all periods.

There are two options for the cluster analysis: applying it to each period separately (implying 258 observations) or pooling the data in the three periods and conducting one overall cluster analysis (implying 774 observations). The former approach is better suited to examine whether the regional characteristics that jointly define typical innovation-weak regions change over time. The latter approach is better suited to examine whether regions change their characteristics, and thus their type, including the main barriers to innovation. Consequently, we decided to apply both approaches.

4 | RESULTS

In this section, we present the results of the cluster analysis. First, we show the correlations found between the characteristics used. Second, we illustrate the identified (number of) clusters on the basis of silhouette plots. Third, we describe the characteristics of the six cluster region types. Fourth, we analyze the change of clusters over time. Fifth, we have a look at the changes in cluster membership of the regions over the study period.

4.1 | Correlation analysis

As a first step, we analyze which of the regional characteristics that might signal barriers to innovation occur together. Table 5 presents the results of the simple correlation analysis.

The variable *INNO* is significantly positively correlated to all other variables, confirming the assumption that all used variables represent regional characteristics that might hinder innovation activities. Most correlations are rather weak and of similar size (between 0.2 and 0.3), except the correlations with the industrial structure (*STRUCT*), the economic strength (*GDP*), and the availability of skilled labor (*SKILL*). Since industrial structure measures, among other aspects, the presence of innovative industries, the high correlation of *INNO* with this variable is not surprising. The strong correlation between *GDP* and *INNO* confirms that innovation and economic development are strongly

**TABLE 5** Correlations between the variables.

	INNO	SCIENCE	spDENS	TRANS	QUAL	STRUCT	GDP	LARGE	FOUND	SKILL
INNO	1.00	0.25	0.22	0.29	0.29	0.63	0.57	0.26	0.22	0.42
SCIENCE	0.25	1.00	0.86	0.57	0.50	0.28	0.30	0.20	0.38	0.06
spDENS	0.22	0.86	1.00	0.57	0.34	0.28	0.24	0.25	0.30	0.11
TRANS	0.29	0.57	0.57	1.00	0.50	0.30	0.38	0.32	0.37	0.06
QUAL	0.29	0.50	0.34	0.50	1.00	0.44	0.37	0.23	0.32	-0.06
STRUCT	0.63	0.28	0.28	0.30	0.44	1.00	0.55	0.46	0.13	0.37
GDP	0.57	0.30	0.24	0.38	0.37	0.55	1.00	0.50	0.34	0.32
LARGE	0.26	0.20	0.25	0.32	0.23	0.46	0.50	1.00		0.16
FOUND	0.22	0.38	0.30	0.37	0.32	0.13	0.34		1.00	0.08
SKILL	0.42	0.06	0.11	0.06	-0.06	0.37	0.32	0.16	0.08	1.00

connected. Although skill shortage is an innovation barrier, the strong correlation between *SKILL* and *INNO* is surprising. However, the finding only signals a connection, not a causal relation.

Most of our regional characteristics are also significantly positively correlated with each other, which shows that indeed various barriers are likely to occur together on a regional level. Most strongly correlated are the population density (*spDENS*) and the presence of scientific research (*SCIENC*). Of course, scientific institutions are rarely present in rural areas. Further correlations above 0.5 are found between the transport infrastructure (*TRANS*) and both population density and scientific activity. Population density and transport infrastructure have both been chosen as indicators for rural areas. The correlations suggest that the innovation barriers connected to the rural regions and research-weak regions might occur often together. Another correlation above 0.5 is found between GDP and industry structure, which have both been declared as measures for lagging regions.

Additionally, the availability of skilled labor is the only variable that is not significantly correlated to several other variables. Correlation coefficients of above 0.3 are found only with *GDP* and *STRUCT*, confirming our use of these variables as an indicator for lagging regions. Nevertheless, the lack of skilled labor seems to be an independent factor.



Hence, the correlation analysis shows that population density (*spDENS*) and transport infrastructure (*TRANS*) measure similar things so that we add the respective (normative) values together forming a new variable *URBAN*. The same holds true for GDP and industrial structure (*STRUCT*), which are combined to a new variable *ECON*. Although scientific activity is also strongly correlated to population density and transport infrastructure, we keep it separate because it represents a different factor according to our theoretical considerations. As a robustness test, all analyses are also conducted using all variables, leading to similar results and especially the same classes of regions.

4.2 | Identified clusters

Independent of whether the periods are pooled or analyzed separately, the silhouette plots indicate the existence of two clusters. Building these two clusters leads in all cases to one cluster of regions for which all characteristics are positive (above German average) and one cluster of regions for which all characteristics are negative (below German average). This shows that a clear difference exists between economically and structurally well-endowed regions and rather lagging regions in Germany. However, this separation is not relevant for our research context.

Therefore, we use a partition into more than two clusters. Most relevant for our analysis is the pooling of all periods and the latest period. The silhouette plot for the pooled data (Figure 1a) shows that besides two clusters,

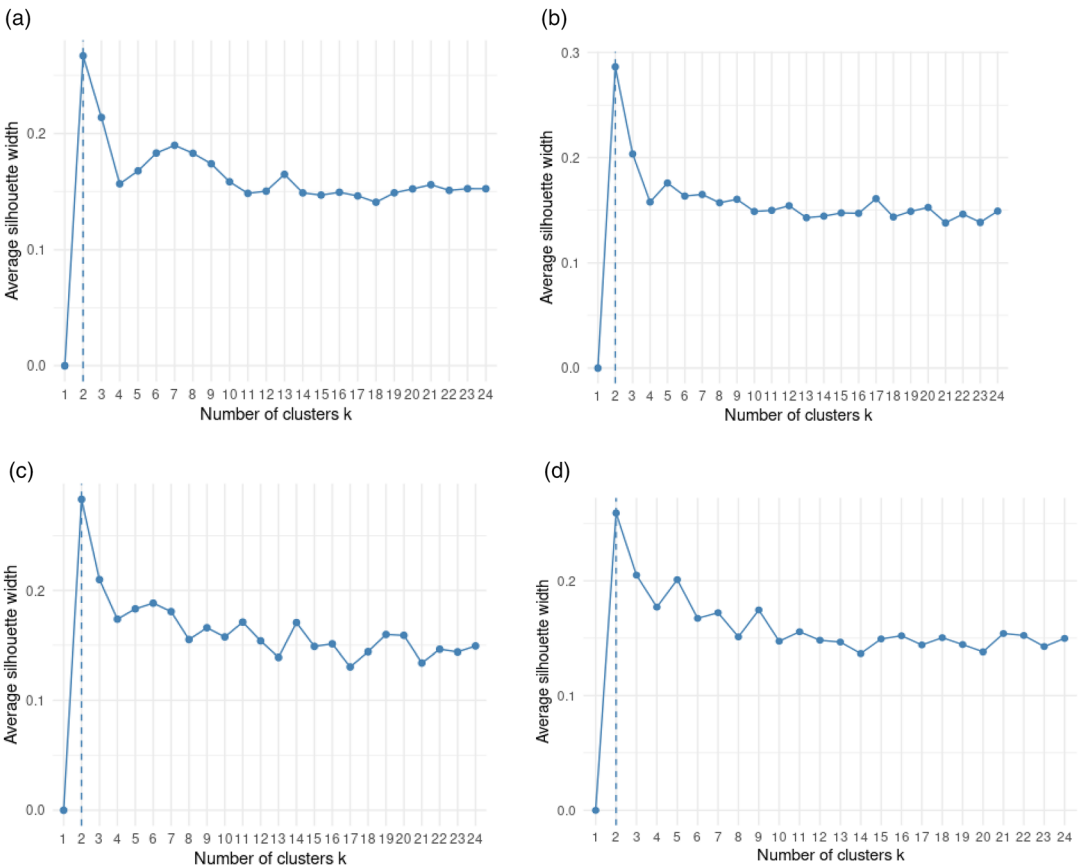


FIGURE 1 Silhouette plots for (a) all periods pooled, (b) the period 2002–2007, (c) the period 2008–2013, and (d) the period 2014–2019.



7 or 13 clusters are also a good choice. The silhouette plot for the latest period (Figure 1d) signifies five or nine clusters as good choices.

We tested the different possibilities and found that choosing nine clusters for the latest period serves our aim the best. Choosing five clusters leads to a lower stability of the clusters over and a separation of the interesting lagging regions into only two clusters, which provides less information. In the case of the pooled data, 7 and 13 clusters are used. The resulting assignments of the labor market areas are depicted in Figure 2. Since there is no way to represent the quality of the result of a clustering approach, we at least provide in Table 6 the share of variation of the regional characteristics that falls between the clusters in Table 6, and the share of this variation that is contained with each cluster. The distribution of all variable values is given in Figures A1–A3.

The maps of the clusters (Figure 2) show some similarities in the classification of regions, although different periods and different numbers of clusters are used. This is further examined in the next section.

4.3 | Related characteristics in clusters

Our main interest is to examine whether certain regional characteristics related to innovation barriers occur frequently together. The above correlation analysis has shown that there is a positive but relatively weak correlation between all characteristics (between 0.2 and 0.3 in most cases), which reflects the finding of a clear difference between more urban/central, economically strong regions and more rural/peripheral, economically weak regions. Now we analyze whether there are groups of regions that show specific co-occurring characteristics. Next, the clusters identified above are analyzed separately. The basis for this analysis is the three clustering results presented above: 7 clusters including all periods, 13 clusters including all periods, and 9 clusters for the most recent period 2014–2019. The three different clustering approaches are used to also examine whether the identified types of clusters are robust concerning their exact setting. The analysis is based on the centroids of the clusters, which represent the average values of the characteristics for each cluster.

Several clusters show average innovation activities above the German average (these are the dark green, green, lighter green, and lighter blue clusters in Figure 2). These are not of further interest for this paper since we focus on innovation barriers in innovation-weak regions. Therefore, we discuss all other clusters in the order of decreasing average innovation activities.

Cluster A (urban hinterland, dark blue clusters in Figure 2):

In this cluster, most characteristics are nearly average. Three weaknesses appear together: low share of large firms, low economic activity, and low share of qualified employees (see Figure 3). This implies that firms are missing a good basis for innovations due to the lack of financial means in small firms and the presence of less dynamic industries (low qualification rate of employees). The respective map shows that most regions of this type are near to larger cities. Therefore, we call them urban hinterlands. The innovation activities in these regions might be overestimated by our approach because many inventors might live in these regions but work in the nearby centers.

Cluster B (old industrialized regions, cyan clusters in Figure 2):

In this cluster, scientific activity, share of large firms, and urbanity are above the German average, while economic strength, innovation activity, and qualification are slightly below average, and founding activity is well below the average. This kind of region is found in Germany mainly in the Ruhr area (see Figure 4).

Cluster C (attractive periphery, [dark] violet clusters in Figure 2):

In this cluster, almost all parameters are below average, except the skill availability. The shortage of skilled workers is a lower issue than in other regions. Furthermore, the number of large companies is roughly in line with the average for Germany as a whole. The regions in this cluster are characterized by a relatively low qualification of the workforce, low research activity, and a below-average propensity to start new businesses. The regions in this cluster are located in peripheral areas (see Figure 5). Nevertheless, they contain some economic and innovative activity and seem to have less of a problem acquiring skilled labor.

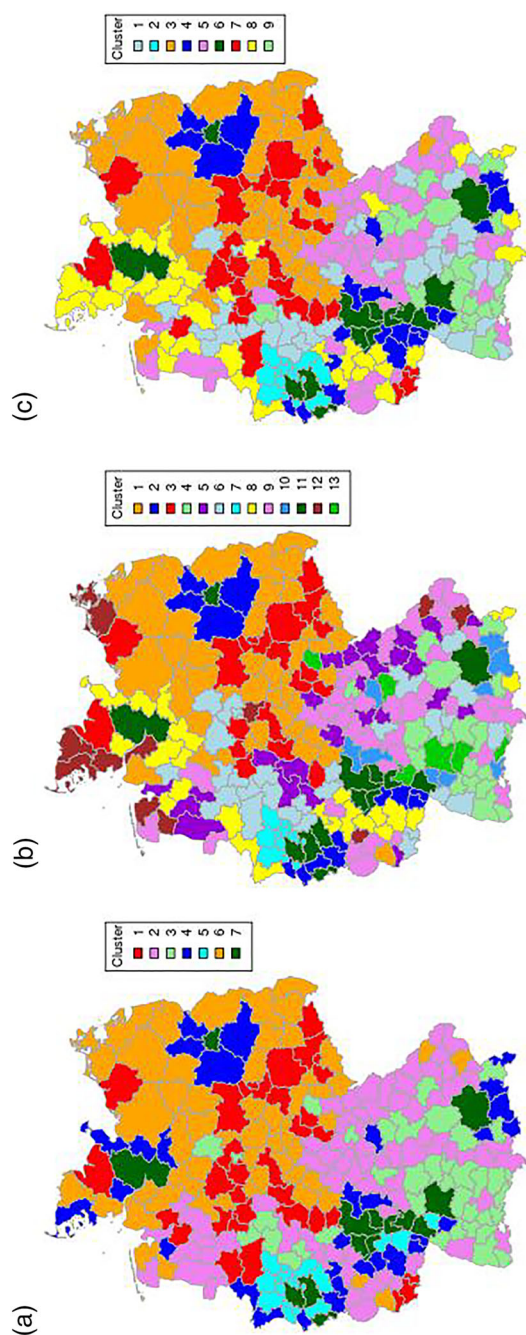


FIGURE 2 Cluster assignment of the labor market regions in 2014–2019 for the clustering including all periods, identifying (a) seven clusters and (b) 13 clusters and for (c) the separate clustering of period 2014–2019.



TABLE 6 The shares of the variation of regional characteristics between clusters and within clusters for the three clustering approaches.

Period	Number of clusters	Between sum of squares/ total sum of squares	Within sum of squares/total sum of squares for cluster					
			1	2	3	4	5	6
2002–2019	13	65.3%	4.1%	1.6%	3.1%	2.8%	1.8%	2.4%
2002–2019	7	56.0%	4.7%	2.5%	10.2%	6.6%	5.5%	7.6%
2014–2019	9	61.9%	2.2%	5.2%	4.0%	5.6%	3.5%	4.6%

TABLE 6 (Continued)

Period	Within sum of squares/total sum of squares for cluster						
	7	8	9	10	11	12	13
2002–2019	1.8%	1.9%	2.9%	1.9%	3.9%	3.5%	3.1%
2002–2019	6.8%	–	–	–	–	–	–
2014–2019	5.6%	4.3%	3.1%	–	–	–	–

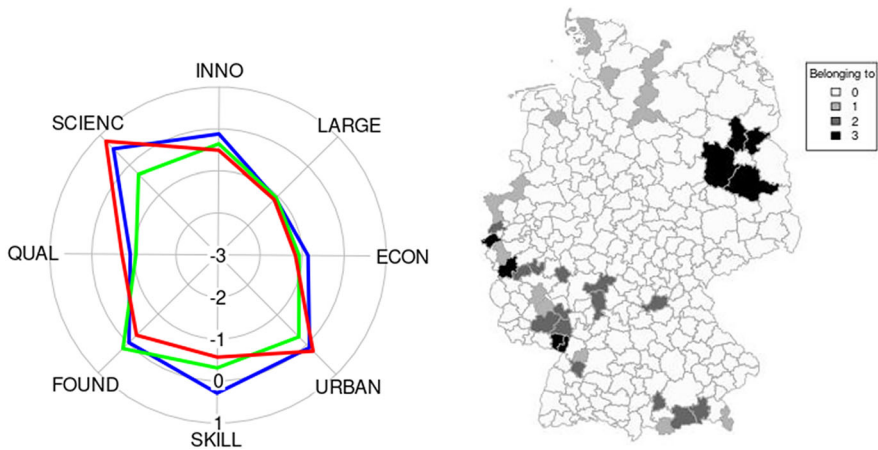


FIGURE 3 Average characteristics of cluster A (blue: 2014–2019; green: seven clusters all periods; red: 13 clusters all periods) and localization of regions belonging to cluster A (light gray: region falls into cluster A in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

Cluster D (skill-shortage regions, red clusters in Figure 2):

In this cluster, the most negative characteristics are the shortage of skilled workers and the propensity to start new businesses. The qualification of the workforce and the share of large companies are average (see Figure 6). Hence, these regions are attractive for large firms and qualified production. However, they are not similarly attractive for workers and founders, which hinders development. Many medium-large cities fall into this cluster, suggesting that these regions, which have been rather average economically, could be falling behind.

Cluster E (peripheral hinterland, yellow clusters in Figure 2):

In the seven-cluster classification for all periods, this cluster of regions does not exist. The respective regions fall mainly into cluster A but also into clusters C, D, and F. This means that the regions have some similarities with those from other clusters, especially those of cluster A. The proportion of qualified employees is even lower than in

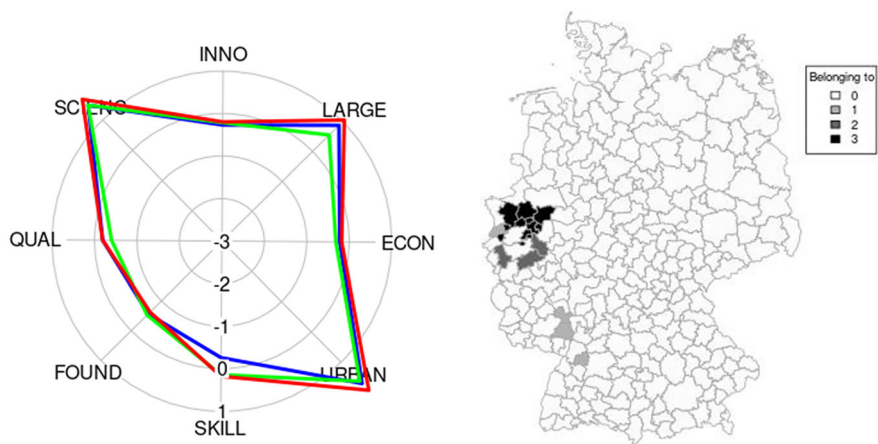


FIGURE 4 Average characteristics of cluster B (blue: 2014–2019; green: seven clusters all periods; red: 13 clusters all periods) and localization of regions belonging to cluster B (light gray: region falls into cluster B in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

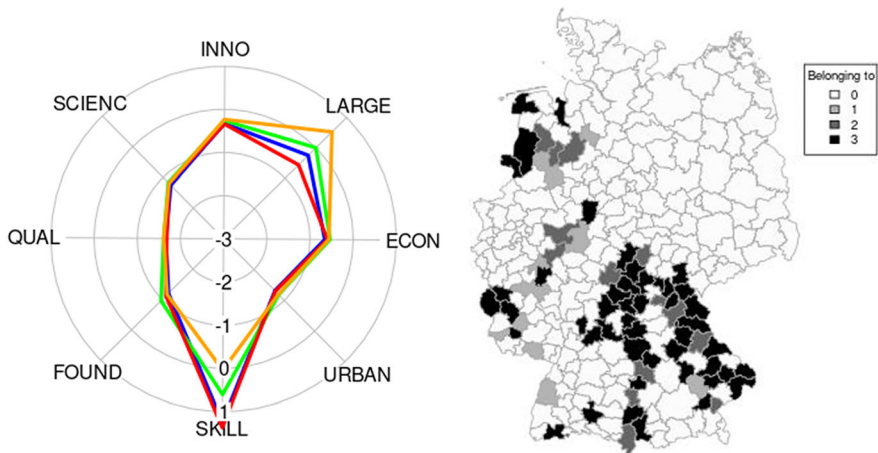


FIGURE 5 Average characteristics of cluster C (blue: 2014–2019; green: seven clusters all periods; red/orange: 13 clusters all periods) and localization of regions belonging to cluster C (light gray: region falls into cluster C in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

cluster A and represents the most negative aspect. There are also a few large companies and an overall weak economy as well as a lack of scientific institutions. The propensity to start a business, on the other hand, is only slightly below average. Most of these regions are near big cities but are slightly farther away than those in cluster A (see Figure 7).

Cluster F (peripheral lagging regions, orange and brown clusters in Figure 2):

This cluster is far below average in all characteristics (see Figure 8). The lowest innovativeness is also found in these regions. Due to the lack of companies, the shortage of skilled workers seems to be a rather subordinate problem. The regions in this cluster are remote, not innovative, and distinctly economically weak. Only in part of these regions might the firm founding activity be seen as a positive sign.

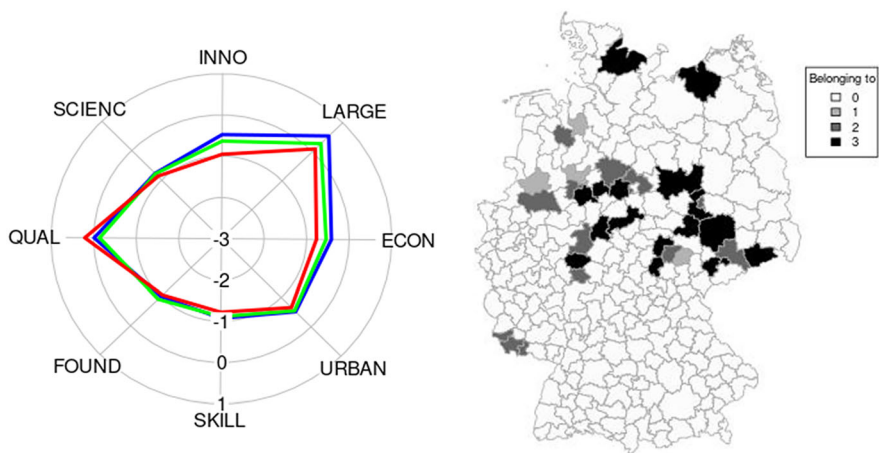


FIGURE 6 Average characteristics of cluster D (blue: 2014–2019; green: seven clusters all periods; red: 13 clusters all periods) and localization of regions belonging to cluster D (light gray: region falls into cluster D in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

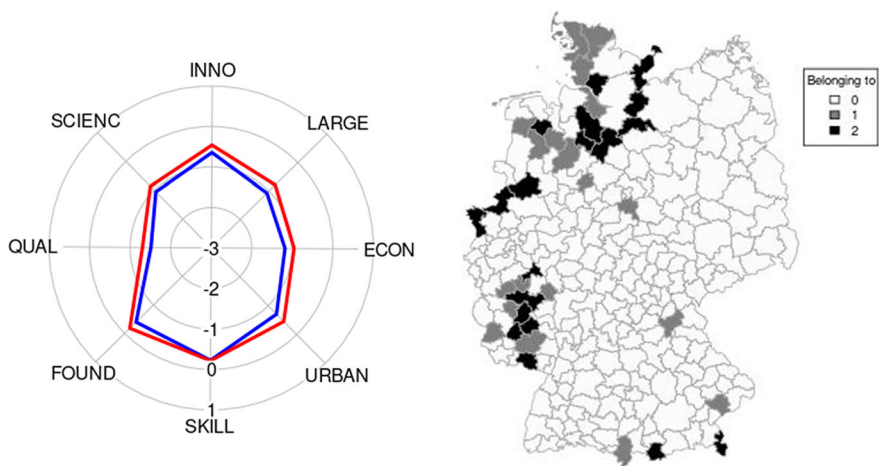


FIGURE 7 Average characteristics of cluster E (blue: 2014–2019; red: 13 clusters all periods) and localization of regions belonging to cluster E (light gray: region falls into cluster E in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

Overall, the analysis shows that indeed several weak characteristics occur together, allowing for a characterization of distinct types of innovation-weak regions. This classification is quite robust, using different periods and numbers of clusters. Table 7 presents the characteristics of these cluster types of regions.

Comparing the empirical results with the theoretical considerations in Section 2.4 shows some correspondence. Cluster A fits well to the regional type R1, which is dominated by small firms, while cluster B fits the regional type R2, which is dominated by large firms. Cluster C is a mixture between the research-weak part of R5 and R6, which is characterized by low founding activity. However, these three types show an innovation activity that is only slightly below the German average, so that these characteristics do not strongly hinder innovativeness. Cluster F is the combination of region types R3 and R4, characterized especially by being rural and economic lagging. This combination seems to constitute a strong barrier to innovation. Cluster D matches region type R6, while cluster E matches region

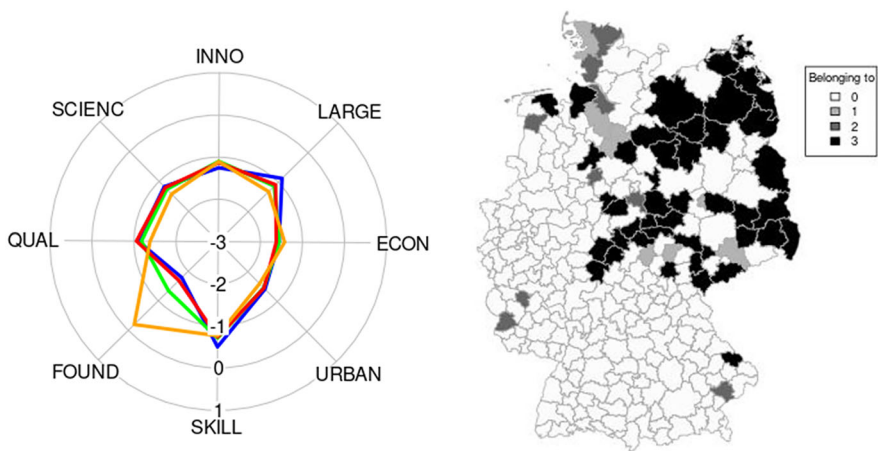


FIGURE 8 Average characteristics of cluster F (blue: 2014–2019; green: seven clusters all periods; red/orange: 13 clusters all periods) and localization of regions belonging to cluster F (light gray: region falls into cluster F in only one cluster variant of Figure 2; gray: two cluster variants of Figure 2; dark gray: all three cluster variants of Figure 2).

TABLE 7 Average regional characteristics for the six low-innovation clusters (classified as ++: 0.5; +: 0–0.5; o: –0.5–0; –: –0.5 to –1; ---: –1 to –1.5; ----: <–1.5; the defining characteristics are presented large and bold).

Cluster	Denomination	INNO	SCIENC	QUAL	FOUND	SKILL	URBAN	ECON	LARGE
A	Urban hinterland	o	+/-	-/--	o	+/-	o	-/--	--
B	Old industrialized regions	o	++	o	–	o/+	++	o	++
C	Attractive periphery	o	--	----	--	+/+ +	--	–	+/-
D	Skill shortage regions	–	–	o/+	--	--	–	o/-	+
E	Peripheral hinterland	–	-/--	--	o	o	–	--	-/--
F	Peripheral lagging regions	--	--	--	-/----	–	--/-	--/----	-/--

Note: INNO: F; Science: C; Qual: A,B,C,E; Found: B,C,D,F; Skill: D; Urban: C,F; Econ: A,B,E,F; Large: A,E.

type R4, both with an innovativeness clearly below the German average. Hence, the theoretical considerations in Section 2.4 are largely confirmed. All postulated types of regions are somehow found in reality, although some of them not in their pure type but only in combinations of the theoretically postulated characteristics.

4.4 | Stability of clusters over time

We previously argued that six innovation-weak clusters are relatively robust when applying clustering approaches considering different specifications. Now we want to check whether these clusters are stable over time. To this end, we apply the cluster analyses to the three periods separately by using the fixed number of nine clusters. The spatial distribution of the clusters shows some stability but also some changes (Figure 9).

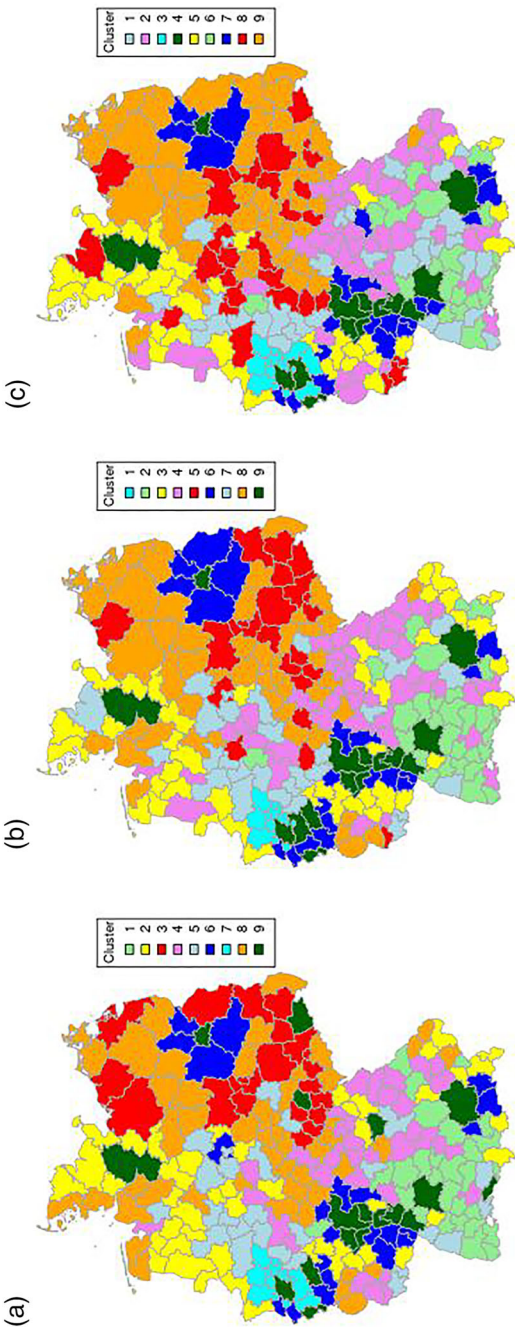


FIGURE 9 Cluster assignment of the labor market regions for the periods (a) 2002–2007, (b) 2008–2013, and (c) 2014–2019.



In contrast to the changes in the assigned regions, the average cluster characteristics are stable (Figure 10). The main changes are found in skill shortage, which has increased tremendously within the considered time span and seems to have affected the regions within the same cluster differently. This is an interesting topic for further research and will be taken up also in the next section. Furthermore, we observe some changes in the founding activity. The only cluster with clear changes in more than these two variables is cluster D, which also shows the most regional changes in Figure 9. The changes in the regional composition of the other clusters seem to not impact the defining characteristics of these clusters.

Consequently, the cluster types, except cluster D, seem to be very stable over time, so that we can indeed assume that specific combinations of regional-innovation-relevant characteristics occur frequently. In this respect, policies and the responsible politicians in the respective regions could use our types of regions as a starting point for their measurements. This means that tailor-made region-type-specific measures or generally a region-type-specific conception of funding programs could be very beneficial. The types of regions presented offer a meaningful and fine-grained classification of lagging regions through the stability depicted, while at the same time not getting lost in the small scale.

4.5 | Change of cluster assignments of regions

To study the stability of the cluster assignments of regions, we include all three periods in one clustering process. By following this approach, one set of clusters is defined, and the regions are assigned to this separately for each of the three periods. Consequently, we can examine whether regions change their cluster assignment with time and which changes in the regional characteristics are responsible for this movement between clusters. Several interesting developments are detected when pursuing this approach. This is also important for political decision-makers in the respective regions. By looking at the cluster assignment changes of regions, political actors can better understand the developments regarding crucial economic variables in their region and thus better act on and shape regional development.

We previously detected that 7 or 13 clusters can be built considering all periods. We use the classification of seven clusters in the following because it is sufficient to understand the occurring dynamics and reduces the number of cases to be discussed compared with the 13-cluster analysis. The assignment of the regions to these seven clusters for the three periods is depicted in Figure 11.

Figure 11 shows that over time there are some movements of regions from one cluster to another. This is in line with the finding in the last section (Figure 9) that applying the clustering to each period separately leads to some changes in the regional composition of the clusters. However, this contrasts with the fact that the average values of the clusters remain very stable over time. To shed light on these issues, we examine all regions that change their cluster assignment between the period 2002–2007 and the period 2014–2019. Thus far, we have only named and discussed the clusters with low innovativeness in detail. In the following, the high-innovation clusters also play a role. Consequently, the cluster colored in green in Figure 11 is denoted as cluster G, and the cluster colored in dark green in Figure 11 is denoted as cluster H in the following.

A total of 65 of the 257 regions change their classification from the first to the last period. Tables 7–10 group these changes according to clusters between which the regions switch. Furthermore, these three tables also present the average values of the regional characteristics for each changing group and the two periods. For the discussion, we build four tables and discuss them separately. We find that many moves are related only to changes in skill availability, with all other characteristics remaining stable, except for some smaller changes in the founding activity. All these cases are presented in Table 9. Similarly, many moves are triggered by a strong decrease in the founding activity, connected to changes in skill availability and partly in qualification. These cases are presented in Table 10. We also separately discuss the moves from the very innovative cluster H to the less innovative clusters (Table 11). All other cases with quite different changes in the characteristics and only one or two cases of the same movement

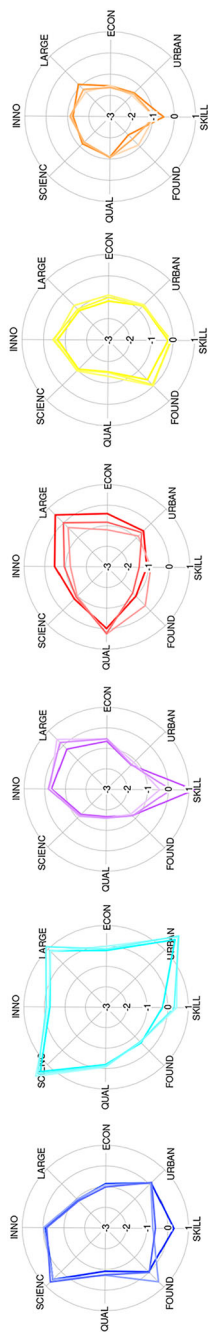


FIGURE 10 Average cluster characteristics for the six clusters (in order, A to F) and the periods 2002–2007 (light color), 2008–2013 (medium color), and 2014–2019 (darkest color).

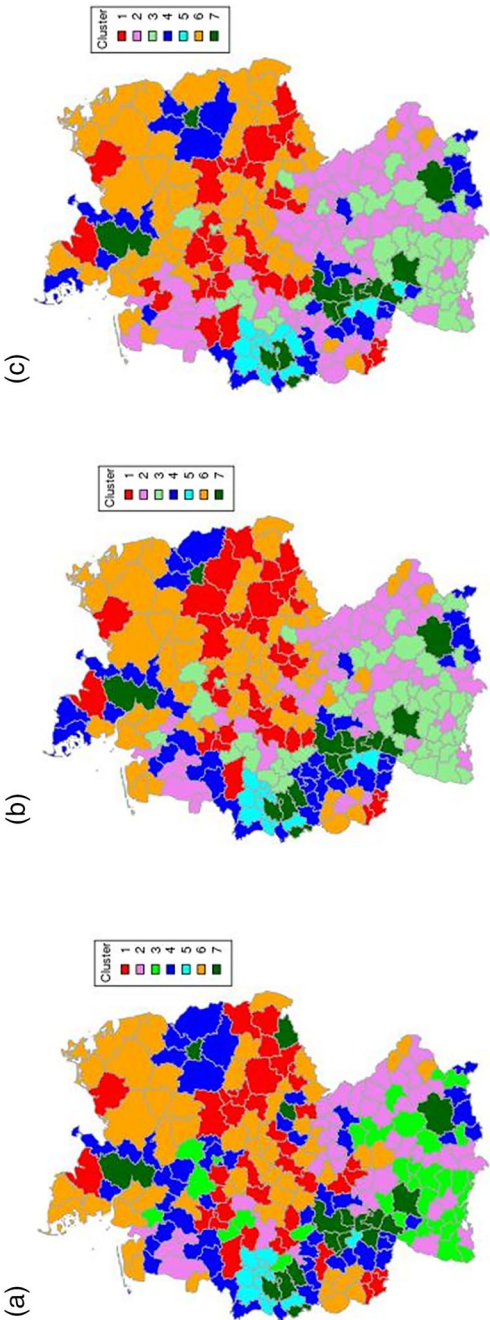


FIGURE 11 Cluster assignment of the labor market regions for conducting the cluster analysis on all periods together. The maps present the assignments for the periods (a) 2002–2007, (b) 2008–2013, and (c) 2014–2019.



TABLE 8 Region-specific changes in cluster assignments of regions from 2002–2007 to 2014–2019 (red and black lines in the radial plots represent the average values of the regional characteristics in 2002–2007 and 2014–2019, respectively).

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (locations)
G → B	2		Pforzheim Gummersbach	
G → C	1		Burghausen	
B → G	1		Lüdenscheid	
F → D	1		Korbach	



TABLE 8 (Continued)



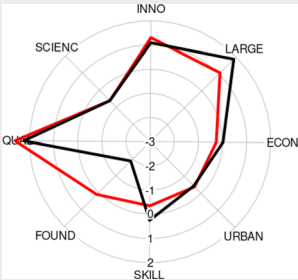

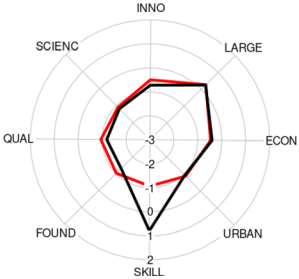

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (locations)
F → A	1		Husum	
H → G	1		Jena	

TABLE 9 Skill-shortage implied changes in cluster assignments of regions from 2002–2007 to 2014–2019 (red and black lines in the radial plots represent the average values of the regional characteristics in 2002–2007 and 2014–2019, respectively).

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (locations)
D → C	9		Siegen Fulda Koblenz St. Wendel Kitzingen Lohr am Main Eisenach Gotha Pößneck	

(Continues)



TABLE 9 (Continued)

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (locations)
D → G	3		Olpe Soest Würzburg	
F → C	13		Wetzlar; Nordholm; Idar-Oberstein; Bernkastel- Wittlich; Daun; Bitburg; Freyung; Ansbach; Neustadt/Aisch; Bad Kissingen; Suhl; Meiningen; Sonneberg;	
C → G	3		Schwäbisch Hall Balingen Coburg	
G → D	2		Hannover Bremen	



TABLE 10 Founding-induced changes in cluster assignments of regions from 2002–2007 to 2014–2019 (red and black lines in the radial plots represent the average values of the regional characteristics in 2002–2007 and 2014–2019, respectively).





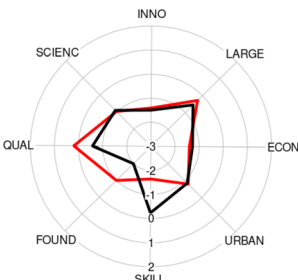

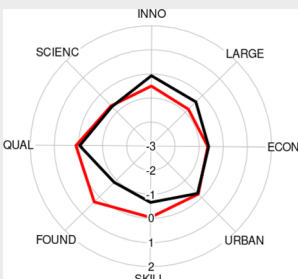

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (location)
A → C	6		Sulingen Verden Osnabrück Montabaur Pirmasens Bayreuth	
A → F	8		Goslar Helmstedt Stadthagen Celle Soltau Leer Frankfurt/Oder Gera	
D → F	4		Cottbus Bautzen Meißen Salzlandkreis	
A → D	6		Braunschweig Oldenburg Steinfurt Gießen Weimar Arnstadt	



TABLE 11 Changes from cluster H to low-innovate clusters of regions from 2002–2007 to 2014–2019 (red and black lines in the radial plots represent the average values of the regional characteristics in 2002–2007 and 2014–2019, respectively).

Cluster change	Number of cases	Average characteristics	Regions (names)	Regions (location)
H → D	1		Dresden	
H → B	3		Leverkusen Bonn Ludwigshafen	

between clusters are presented in Table 8, and are not further discussed because these cases seem to represent specific and not general developments.

Table 9 presents 30 cases in which all regional characteristics remain relatively stable over time except the *SKILL* variable and sometimes the *FOUND* variable. In 28 cases, skill availability has increased strongly. The basic reason for these changes is the strong increase in skill shortage that Germany experienced within the last 10 years. The number of days that it takes to fill free qualified positions increased from 65 in the first period to 75 in the second period and 102 in our third period. Since we calculated our variables relative to the average within each period, the *SKILL* variable varies around zero for all periods. The changes in this variable for a region result from a higher or lower increase in skill shortage relative to the German average.

Hence, the identified 28 cases of regions that change their cluster assignment due to an increase in the *SKILL* variable are regions that have been less hurt by skill shortage in recent years compared with others. Many of them moved to cluster C, which is characterized by an above-average availability of skilled labor. This also matches the strong increase in the *SKILL* variable that we observe for cluster C when clustering each period separately (Figure 10). Most regions that show this change are smaller and medium-large cities with a low share of qualified employees (Table 9). To sum up, many regions do not require a large amount of qualified labor, and are thus less hurt by skill shortage. This fits findings from Coad et al. (2016:328) that companies ‘with more highly educated employees are more likely to face problems of “lack of qualified personnel”’. Our findings cause a change in cluster assignments without clear changes in the other variables. The opposite effect is only observed in two cases (last row in Table 9).



There are additional regions that show strong changes in the relative skill availability, but in these cases, there is also a strong decrease in the founding activity. Table 10 presents all cases with such a strong decrease in the FOUND variable. In 18 cases, we observe the combination with an increasing skill availability, while in six cases skill availability decreases. Four of the former cases also display a strong decrease in qualification, and the other eight cases show a smaller but still visible decrease in qualification. We can conclude that in these 24 regions, the economic dynamics (founding activity) have decreased, partly combined with lower qualification requirements. Most of these regions have been classified as urban hinterlands in the first period and developed during the observed time into regions with peripheral characteristics. These regions have already been the more peripheral regions within the urban hinterland group before (including medium-sized cities outside or at the edge of metropolitan areas as well). However, the findings suggest that these regions continue losing attractiveness, especially regarding founding activities. Since new firms are an important engine for future economic development, these regions are likely to fall further behind. This will lead to increases in inequality between the economically successful and lagging regions.

Finally, there are four cases in which regions that have been classified into the highly innovative cluster H move to one of the less innovative clusters (Table 11). Again, a reduction in founding activities is, on average, the most important change. This adds to the previous discussion since several relatively urban regions have experienced a strong decrease in founding activities, despite the strong support of start-ups in Germany. It can be expected that this will have negative impacts on the future economic development in these regions.

5 | CONCLUSIONS

The paper aimed to classify German regions according to present innovation barriers. Combining the regional innovation system concept with findings on innovation barriers in firms, we developed a theoretical classification of regional barriers to innovation. With a statistical clustering approach, we show that distinct types of regions can indeed be identified. While the assignment of regions shows some dynamics, the identified types are found to be relatively independent of the studied period and variations in the number of clusters. Hence, we can claim that at least in Germany, various types of regions exist that are less innovative for different reasons.

This finding has consequences for region-specific policy. We argue that policy programs that can be formulated are not only region-specific, but can also be applied to many other lagging regions. For example, cluster B (old industrialized regions) contains regions that mainly lack economic dynamics in the form of new firms. Hence, politicians should focus on generating new economic activity in these regions. In addition, policy should support the restructuring of these old industrialized regions and take measures to promote economic diversification (Birch et al., 2010). The development of new regional industrial pathways could be a good option (Hassink et al., 2019). In contrast, regions in clusters A (urban hinterland) and E (peripheral hinterland) are predominantly lacking economically strong, large firms that employ qualified labor. The smaller firms in these regions usually need support in their innovation activity due to limited resources and capacities and an often worse quality of entrepreneurship (Fernández-Serrano & Romero, 2012). Another case is the regions in cluster D (skill-shortage regions). Although many characteristics of these regions are average or only slightly below average, skill shortage is a big issue, and consequently, founding activity is relatively low. This cluster shows that non-peripheral regions might also face strong skill shortage problems and not only peripheral regions due to out-migration (as identified by Meister et al., 2023). Strong competition for skilled workers might be responsible for the skill shortage in such regions, as was found by König (2023), although for a region that is not innovation weak. Our findings suggest that policy must focus on investing and attracting skilled people to the region and motivating them to found new firms in many types of regions, not only peripheral regions. A special case is cluster C (attractive periphery). These regions seem to be attractive for firms and skilled workers but are lacking science institutions and founding activity. Politicians should focus on building research and education facilities in these regions or connecting the firms with such institutions. Doloreux and Dionne (2008) show



in their case study regarding La Pocatière how fruitful the development of an institution-driven RIS in peripheral regions can be. Less clear is the policy situation in regions of cluster F (peripheral lagging regions) because these are comparably weak in all studied aspects. According to Stephens et al. (2013) and Stephens and Patridge (2011) lagging regions also benefit from support programs for entrepreneurship and entrepreneurial development, and this is probably more effective than other knowledge-based policies such as acquiring highly skilled employees and developing high-tech clusters. That could be a probable starting point for policy in these types of lagging behind regions.

Interestingly, the lowest innovativeness is found in regions that are characterized by either a lagging economy (with or without being also rural) or a low founding activity. Hence, these characteristics seem to build the strongest regional barriers to innovation. While the founding activity can and should be supported directly, especially in the regions that are hurt by the lack of firm foundation in their development, the situation is different for regions with a lagging economy. Innovations are one way to improve the economic situation so that we face a vicious cycle here. Less technology-oriented innovation activities, which we have not been able to measure in our approach, might be a solution here. They can be more easily developed in regions with lower technological qualifications and experience.

Our classification of regions is based on observable characteristics that function as barriers to innovation. In individual cases, the same barriers to innovation can have partly different or region-specific reasons. Hence, our approach provides information about what problems have to be dealt with in different types of regions. The way in which these problems are addressed best may vary between regions because the underlying reasons are different. Region-specific analyses – possibly case studies – are adequate to provide more detailed information and recommendation for policy measures. However, this is beyond the scope of this paper.

Additionally, the classification has proven itself to be helpful in identifying crucial dynamics. While the characteristics of the identified classes of regions do change relatively little over time, many regions change their class assignment. Examining these changes revealed two interesting dynamics. First, many lagging regions in Germany are less affected by the recent increase in skill shortage. This is caused by the low requirement of skilled labor in these regions. While this might look like a positive relationship, it rather signals that these regions are not economically dynamic, decreasing their economic development expectations for the future.

Second, many regions experienced a clear decrease in founding activity. These are often regions in the urban hinterland that have not been economically strong in the past. The increase of policy support for start-ups seems to have fallen on fruitful ground, mainly in the economically strong regions. The economically weak, as well as many regions in the middle, have not benefited, and especially those in the middle have lost their relative position as a consequence. Since future developments are strongly influenced by start-ups, the question of how founding activity can be supported and increased in the economically not-so-strong regions is an important policy question identified by our analysis. This is also related to the low presence of skilled people in these regions.

While our approach has provided relevant and interesting results, our study region was limited to Germany. It would be interesting to see whether similar types of less innovative regions exist in other countries as well. Furthermore, it would be interesting to know whether the dynamics found and described in this paper are also present in other countries. Consequently, future research should pursue the same approach in other countries to test its feasibility and to gain more insights. Furthermore, case studies are needed to examine the mechanisms behind the identified innovation barriers on the regional level. Such additional insights would then also allow for the development of the theoretical concept of regional innovation barriers further and in more detail. Hence, this paper can be seen as a first step toward establishing a classification of regions on the basis of regional innovation barriers and providing a theoretical foundation for place-type-based policy measures.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the result.

ORCID

Tobias Johannes Hertrich  <https://orcid.org/0000-0002-0199-6888>

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APPENDIX A

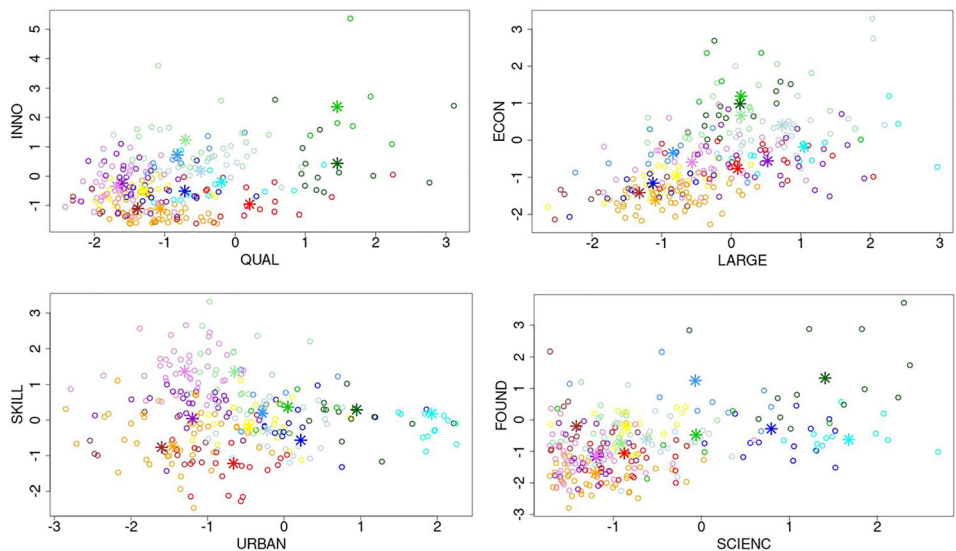


FIGURE A1 Indicator values for all regions colored by their cluster assignment in the joint clustering of all periods with 13 clusters (average values for the clusters are marked by stars).

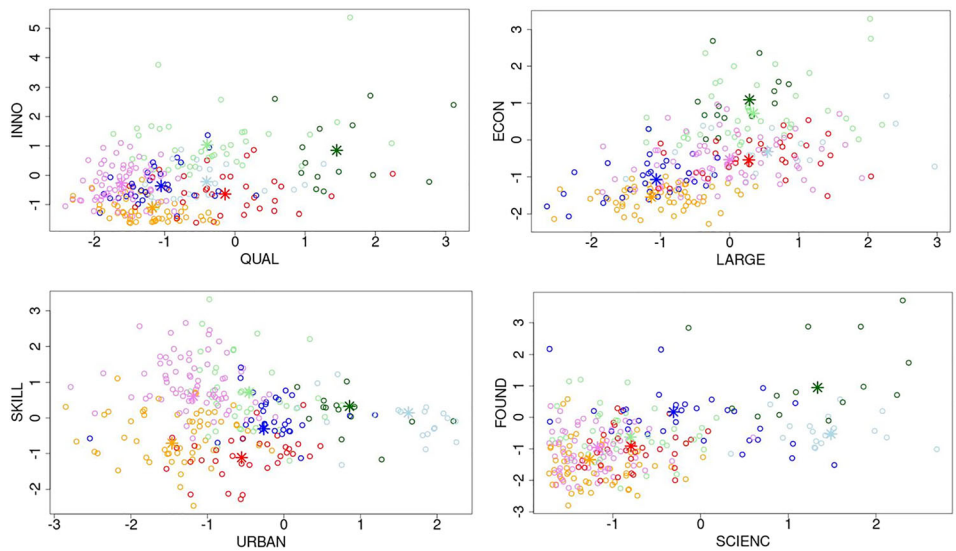


FIGURE A2 Indicator values for all regions colored by their cluster assignment in the joint clustering of all periods with seven clusters (average values for the clusters are marked by stars).

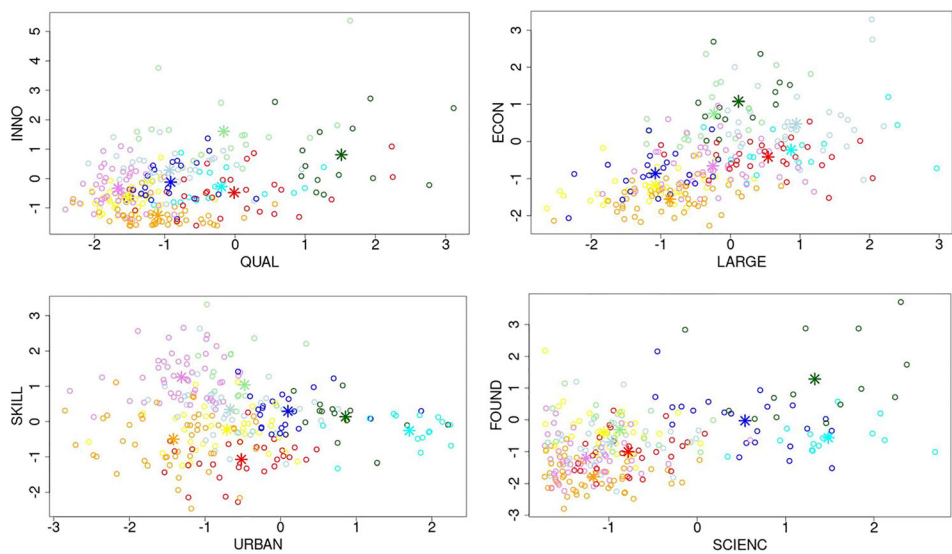


FIGURE A3 Indicator values for all regions colored by their cluster assignment in the clustering of period 2014–2019 with nine clusters (average values for the clusters are marked by stars).



Resumen. Las regiones rezagadas difieren en sus características, lo que implica la necesidad de medidas políticas a medida para mejorar la situación económica de estas regiones. Sin embargo, aunque existen diferencias entre estas regiones, pueden existir ciertos tipos de regiones que comparten los mismos obstáculos a las innovaciones, lo que permite tomar medidas políticas similares. Este artículo examina si es posible identificar este tipo de regiones en Alemania, qué características poseen y cómo cambian. Para ello, se identifican y operacionalizan las características regionales relacionadas con las barreras a la innovación. A continuación, se realiza un análisis de conglomerados para el área del mercado laboral alemán. Aunque los tipos de regiones identificados se discuten también en la literatura de una u otra forma, el artículo proporciona por primera vez una clasificación dentro de un marco empírico y permite estudiar la dinámica de los tipos de regiones, así como la dinámica en cada región dentro de este marco. La correspondencia con los conocimientos existentes sobre las regiones alemanas confirma que es posible hacer una clasificación de este tipo utilizando datos cuantitativos. Además, la estabilidad de los tipos de regiones confirma que dicha clasificación puede considerarse una buena base para las medidas políticas. Los resultados también describen tendencias que podrían plantear problemas en el futuro y requerir atención política.

抄録: 後進地域はその特性が異なるため、地域の経済状況を改善するための政策措置として、その地域特有の政策が必要であると考えられる。これらの地域には違いがあるものの、イノベーションに対する障害が共通している、ある特定のタイプの地域が存在する可能性があり、そうした地域で同様の政治的措置をとることができる。本稿では、このようなタイプの地域がドイツにおいて特定できるか、その地域はどのような特徴があり、どのように変化するかを検討した。この目的のために、イノベーションに対する障壁に関連する地域の特性を特定し、操作化する。次に、ドイツの労働市場地域についてクラスター分析を行った。特定された地域のタイプは研究論文でも何らかの形で議論されているが、本稿は初めて一つの実証的フレームワーク内での分類を提示し、各地域内のダイナミクス及び地域のタイプのダイナミクスの、このフレームワーク内での研究を可能にした。ドイツの地域に関する既存の研究論文への通信により、定量的データを用いてこのような分類が可能であることを確認した。さらに、地域のタイプの安定性は、このような分類が政策措置の良い基礎になると考えられることの裏付けとなる。また、この結果から、将来の問題につながり、政策的な注意が必要となる可能性があることが指摘される。