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Research and development intensive clusters and regional competitiveness

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Abstract

Modern cluster theory provides reasons for positive external effects that accrue from the interaction of spatially proximate firms operating in common and related fields of economic activity. In this paper, we examine the impact of R&D-intensive clusters as a key factor of regional competitiveness on productivity growth. In relying on a hybrid approach of cluster identification, we examine effects of cluster specialization and diversity for a panel of German NUTS-3 regions in 2003–2019. After controlling for regional characteristics and unobserved heterogeneity, a robust cluster strength effect (i.e., specialization) on productivity growth is found within the context of conditional convergence across German regions. With regard to the underlying mechanisms, we find that the presence of multiple R&D-intensive clusters in specific technological fields is most strongly linked to higher levels of regional productivity growth. We also find that advantages from cluster specialization are strongest in key industrial sector such as automobile production, machinery, chemical and pharmaceutical products. Overall, our estimates

Abbreviations: Cov, covariance; CPA, classification of products by activity; CRE, correlated random effects; E, expectation; EA, economic areas; EU, European Union; FE, fixed-effects; GDP, gross domestic product; GRP, gross regional product; H, Shannon's entropy; I-O, input-output; J, measure of evenness; LQ, location quotient; MAR, Marshall-Arrow-Romer; NACE, Statistical Classification of Economic Activities in the European Community; nCl, number of clusters; NUTS, Nomenclature des Unités territoriales statistiques; OLS, ordinary least squares; QIQA, qualitative input-output analysis; R&D, research and development; RE, random effects; REIV, random effects instrumental variables; REWB, within-between random effect; SL, spatial lag; U.S., United States.

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particularly highlight the working of Marshallian externalities in productivity dynamics, while Jacobs-type spillovers tend to be partially realized. These findings indicate that some but not all cluster-based regional development strategies are promising policy tools to foster regional growth processes.

KEYWORDS

cluster diversity, cluster specialization, industry clusters, productivity growth, regional competitiveness

1 | INTRODUCTION

Spatial clustering of economic activity is a worldwide phenomenon that has attracted an unabated interest among academics and policy makers – fuelled by seminal research contributions of influential scholars like Michael Porter (1990, 1998, 2000) and Krugman (1991, 1995), further extended in Fujita et al. (1999). Competitive advantages attributed to groups of firms (and associated institutions) that operate in the same or closely related industries and are co-located within a region can arise in different ways. By pointing out the role of clusters for firm competitiveness and regional development, the cluster concept has been eagerly taken up by policy makers and other regional actors (Brave & Mattoon, 2020; Ketels & Protsiv, 2021; Njøs & Jakobsen, 2016; Slaper et al., 2018; Spencer et al., 2010).

While cluster policy in highly developed areas primarily aims at strengthening the competitive advantages of local firms in global markets, support to cluster formation in lagging regions is mainly targeted at fostering the regions' catching-up processes to their more developed counterparts. The evaluation of the impact of cluster policy is usually confined to selected industry clusters. Case studies on well-functioning clusters are occasionally used to illustrate best practices that could inspire regional planning agencies and decision makers in other industrial environments. While qualitative case studies typically provide a detailed description of cluster actors and their interaction (Schmiedeborg, 2010), they are typically incapable of identifying favorable effects from cluster support activities beyond the specific case studied.

Quantitative research on the impact of clustering on economic activity, drawing on larger samples of firms or regions, primarily focusses on investigating the role played by agglomeration economies on the structural performance of these firms or regions (Slaper et al., 2018). Although all strands of the evaluation literature have to cope with the common problem of adequately identifying regional clusters, the identification task is typically more demanding in quantitative vis-à-vis qualitative analyses, where economic effects from the co-location of economic actors operating in closely related industries are evaluated in a broader territorial context (typically nationwide). To draw generalizable conclusions from quantitative research, clusters in diverse fields of economic activity need to be identified. This is often done at the expense of insights into the underlying network structure and evolution of clusters, which are often at the heart of the qualitative case study approach.

A plethora of studies have been conducted to gain insights on the contributions of initiatives, networking, and support measures for the efficiency of individual clusters (e.g., Wolf et al., 2019 on the supportive role of cluster management for cluster development). Likewise, a large variety of investigations on external effects from general agglomeration patterns of economic activity exist

(Mitze & Makkonen, 2020). However, only scarce evidence is available on the specific agglomeration effects that result from the co-location of actors in closely related industries, that is, clusters. Without controlling for regional characteristics, statistical analyses, as for instance correlation analyses, bear the danger of drawing erroneous conclusions on cluster effects (Spencer et al., 2010). Therefore, the adoption of a proper econometric modeling approach is indicated. A theory-based definition of regional clusters is a prerequisite of a sound empirical identification strategy.

In the last decade, some research papers have started to use a rigorous econometric approach for evaluating the performance of clusters. For instance, Spencer et al. (2010) use four-digit level industries to identify industrial clusters across Canadian city-regions and assess their effects on regional performance. Evidence on supply chain effects on growth performance are provided by Maine et al. (2010). Delgado et al. (2014) have developed a convergence model to evaluate cluster effects on employment and patent growth at the region-industry level. Recently, Slaper et al. (2018) have investigated the strength of cluster effects on regional performance in the United States; Ketels and Protsiv (2021) use data from the European Cluster Observatory to assess the role of clusters for industry-level wages and per capital GDP.

We add to this literature by focusing on the role of cluster effects on economic performance while explicitly controlling for regional covariates, sectoral heterogeneity and general productivity trends for sample regions, that is, convergence or divergence forces. Without cluster effects, lagging areas may catch up to high productive or innovative regions. Yet advanced regions can keep or extend their lead if agglomeration forces through positive cluster effects outweigh convergence forces. And, in turn, backward regions with clustering structures can catch up faster or even outpace initially higher developed regions over time. The complex interplay between agglomeration and convergence has already been addressed in some earlier studies (Alexiadis, 2013, p. 141; Dřrzu, 2013; Guastella & Timpano, 2016; Sonn & Park, 2011).

The present study thus aims at assessing the impacts of research and development (R&D)-intensive industry clusters on regional competitiveness by accounting for potentially countervailing convergence forces. According to the cluster approach, competitive advantages mainly translate into productivity, wage and knowledge growth (cf. Cingano & Schivardi, 2004; Cortright, 2006; Delgado, Porter and Stern 2010; Ketels & Protsiv, 2021). In view of different types of agglomeration advantages from industrial clusters (Njøs & Jakobsen, 2016), we differentiate between impacts of cluster specialization and diversity. By adopting a spatial econometric approach, we allow for region-specific effects and cross-regional spillovers from both types of cluster structures on regional competitiveness proxied through productivity growth as outcome.

The paper is structured as follows. In Section 2 we provide a literature review on cluster agglomeration and regional competitiveness. Section 3 addresses the identification of regional clusters of R&D-intensive industries. In Section 4, the econometric modeling approach for assessing cluster effects on productivity and innovation is outlined. Data sources and variable definitions are given in Section 5. In Section 6, empirical findings of the role of R&D-intensive clusters for productivity dynamics are presented. The final Section 7 concludes the paper and draws some policy implications.

2 | LITERATURE REVIEW

The theory of clusters is marked by different schools of thought embracing a variety of methodological approaches. Bibliometric analyses have started to organize these different strands, concepts and topics of research on industrial clusters in a comprehensive manner (Cruz & Teixeira, 2010; Lazaretti et al., 2014). Because economic clusters entail a geographical concentration of firms and workers, most approaches originate from the field of location and agglomeration theory.

Inside an agglomeration, positive specialization effects are attributable to internal and external economies of scale. Porter's cluster approach does not primarily bear on cost advantages and factor inputs but puts a special emphasis on continuous improvement and innovation as well as a strategic positioning by companies (Martin & Sunley, 2003; Porter, 2000). A cluster is viewed as a group of proximate companies in a particular field that are linked by commonalities and complementarities. Within this close-up network of firms, competition and cooperation take place at the same time ("coopetition"). Competition is expected to prevail among horizontally linked enterprises. Vertical links between firms as well as strategic alliances with universities and research institutions are usually characterized by cooperation on the basis of trust.

Porter's diamond model stresses the role of local competition is conducive for innovation and growth in industrial clusters (cf. Almeida, 2007; Glaeser et al., 1992; Porter, 1998, 2000; Runiewicz-Wardyn, 2013). Positive externalities arise from geographically concentrated core industries along with their related sectors endowed with highly competitive enterprises (Porter externalities). The diamond model indicates that firms' competitive advantages are affected by the local business environments that are determined by input factors and demand conditions, firm strategy, structure, and rivalry, as well as related and supporting industries. Each region has its own particular set of factor conditions that explain its orientation and outcome. Hence, regional competitiveness is deemed to depend crucially on the quality of these mutually interdependent factors. A certain influence of government on factor conditions, for example, on qualification and the regulatory environment, gives a rationale for cluster-based policies.

As a cluster involves a group of firms from a core industry along with actors from related sectors, it is generally recognized that cluster specialization¹ involves more than merely industrial specialization effects. Already with view on the involvement of supply and demand relations, related sectors are more comprehensive than suggested by the literature on within-industry Marshall-Arrow-Romer (MAR) externalities (Henderson, 1997). Also, vertical linkages may be involved in regional clusters by technological commonalities across sectoral boundaries. Thus, cluster specialization partially covers Jacobs-type externalities that can be characterized as related variety (Franken et al., 2007).

On this account, Njøs and Jakobsen (2016) ascribe agglomeration advantages emanating from related variety of industrial clusters as the „middle ground” between MAR and Jacobs externalities. While related variety is inherent to the concept of industry clusters, the match is by no means perfect. Virtually all cluster definitions focus on related industries, but they do not account for all interconnections between sectors. Delgado et al. (2016) underline that different types of relatedness – such as knowledge links, input-output links, skill-based links, co-location patterns of industries or product similarity – are used to define clusters of related industries. Regional clusters therefore always cover related variety to some degree. Although cluster diversity is closely connected to unrelated variety, both concepts are not congruent.

By investigating the role and nature of agglomeration economies from regional cluster, the impacts of cluster strength and cluster diversity on regional competitiveness and growth come into the focus of research (Delgado et al., 2016; Slaper et al., 2018). While cluster specialization is reasoned to be the major driver of productivity growth through incremental innovations, cluster diversity is expected to provide an environment favorable for more radical innovations. However, beneficial cluster effects will likely be offset by certain types of agglomeration disadvantages - at least partially. Congestion, for example, increased environmental pollution and transport costs, represent countervailing dispersive forces. Attached to initial levels of productivity and innovation, forces toward regional convergence can be disclosed. As long as dispersive forces do not prevail, competitive advantages from agglomeration economies in clusters are expected to be in order.²

In the last decade, different econometric approaches have been applied to identify cluster effects on competitive advantages. Spencer et al. (2010) employed economic performance indicators and growth regressions to assess the strength of regional clusters in Canada. Industrial clusters across Canadian city-regions are identified from four-digit level industries based on location quotients. Positive impacts on employment growth were especially found in service-oriented and knowledge-intensive industrial clusters. This does not hold for smaller cities that most notably specialize in resource-based or traditional manufacturing clusters. Ambiguous results are obtained for cluster specialization on innovation growth which may be attributed to different patent-generating functions across industries (Spencer et al., 2010).

Delgado et al. (2014) investigate the importance of cluster effects for job creation and innovation of regional industries in the United States in the presence of convergence. Using data from the U.S. Cluster Mapping Project the authors find cluster strength effects on employment and patent growth. Related clusters in the own region and clusters of similar sectoral type in adjacent regions are found to exhibit positive growth effects in economic areas (EA) industries. Thus, in contrast to other studies on cluster effects, Delgado et al. (2014) take explicitly account of inter-sectoral and inter-regional spillovers from clusters. Focusing on impacts of cluster specialization and related clusters on EA industries, no knowledge is provided about the role of industry clusters on the economic performance of regions.

Different from Delgado et al. (2014), however, the identification approach by Fallah et al. (2014) does not find generally positive cluster strength effects on employment growth across metropolitan and nonmetropolitan U.S. counties. This holds for both overall high-tech employment growth and corresponding non-high-tech categories. While within-industry cluster effects turn out to be significantly negative, spatial spillover effects remain nonsignificant. Also, no knowledge spillovers from universities for nearby firms are found. As opposed to Marshall-Arrow-Romer (MAR) externalities, evidence of beneficial urban agglomeration economies is found for high-tech sectors.

The studies of Maine et al. (2010) and Slaper et al. (2018) aim to disclose effects of both cluster strength and diversity. With this orientation, they impart special insight into the relevance of Marshall-Arrow-Romer (MAR) externalities and Jacobs-type externalities from the perspective of clusters. Slaper et al. (2018) find that traded cluster strength is positive related to productivity growth in U.S. metropolitan areas. Diversification tends to be only advantageous in the case of local clusters. The cluster specialization effects are also found by Maine et al. (2010) for new U.S. technology-based firms. The study is insofar relevant in studying regional contestability as it shows that cluster diversity effects may strongly depend on the involved business sectors. Simultaneous convergence effects are neglected in both studies. Uncovering both types of cluster impacts on regional competition under the occurrence of both conflicting forces thus remains an open task.

Ketels and Protsiv (2021) adopt the cluster identification approach proposed by Delgado et al. (2014) to analyse wage and per capita GDP effects of clusters for NUTS-2 regions in EU countries throughout 2011–14. The results show that cluster presence is significantly and positively related to industry-level wages and, hence, extend earlier findings for the US on job creation, showing that agglomeration both within industries and from surrounding clusters of related industries relates to performance. With regard to regional per capital GDP growth, Ketels and Protsiv (2021) report significant positive GDP effects of cluster strength defined as a measure of how much value creation in a region is driven by clusters for which the region has achieved a critical mass in the EU. In comparison, no effect is found for cluster mix, that is, a measure of differences in the degree of regional specialization, once estimation account for the overall quality of the business environment. Estimations are carried out in a static framework with no account of underlying convergence forces in the EU. The authors also use a relatively broad regional measure (NUTS-2 regions), which may affect the identification of local clusters. Our work complements this first evidence for European data by adopting a dynamic estimation framework and use regional data with a higher degree of spatial granularity.

3 | ECONOMETRIC MODELING APPROACH

In measuring the impact of a (cluster) policy variable or another type of exogenous shock on outcome variables at the firm or regional level, counterfactual “with/without” methods are typically applied (e.g., Garone et al., 2015, 2016; Gertler et al., 2016; Giuliani et al., 2013). These methods are designed to assess the impact of a policy measure (or exogenous shock) by comparing the current situation with the implementation of the policy measure (shock) to the case that would have occurred in its absence. This counterfactual situation can be constructed based on information on the variables of interest in the pre-treatment period.

The situation is different when potential benefits of regional clusters are investigated (Delgado et al., 2014). Different from a policy measure or exogeneous shock, cluster structures do not arise suddenly from a dispersive landscape but develop gradually over time along their life cycle (cf. In Fornahl & Hassing, 2017; Menzel & Fornahl, 2010). Once established, they persist over years until they may (potentially) completely disappear at the end of their maturity stage. We make use of the only gradual time-varying (i.e., quasi exogenous) nature of established cluster structure to use panel data models that allow us to account for unobserved regional characteristics and transregional trends in evaluating cluster effects.

We adopt a spatial panel data approach to investigate the impacts of regional clusters of R&D-intensive industries on regional competitiveness. The simultaneous existence of opposing forces may be rationalized at the region-industry level (Delgado et al., 2014), but there is an extensive literature that substantiates convergence at the regional level (cf. Islam, 1995; Sala-I-Martin, 1996). Both economic forces can be effective at the same time. Regions may benefit from diverse cluster advantages while converging to their own steady states. On the other hand, disadvantages of clustering in the form of congestion effects may harm regional economic performance.

According to the above reasoning, we specify the regional productivity growth model for assessing impacts of R&D-intensive clusters to have the following form:

$$\log\left(\frac{y_{i,2003,4,h}}{y_{i,2003+4,(h-1)}}\right) = \delta \cdot \log(y_{i,2003+4,(h-1)}) + \sum_{l=1}^m \gamma_l \cdot Cl_{li,2006} + \sum_{l=1}^m \gamma_l^* \cdot SL(Cl_{li,2006}) + \sum_{j=1}^k \beta_j \cdot x_{ji,2003+4,(h-1)} + \alpha_i + u_{i,2003+4,h} \quad (1)$$

with $i = 1, 2, \dots, 402$ regions and $h = 1, \dots, 4$ periods. The convergence model (1) explains productivity growth in region i in the period 2003–2019, $\log\left(\frac{y_{i,2003+4,h}}{y_{i,2003+4,(h-1)}}\right)$, by its initial productivity level, $\log(y_{i,2003,4,(h-1)})$, the presence of cluster effects from the own region i , $Cl_{li,2006}$, and spatial cluster effects $SL(Cl_{li,2006})$ from cluster activities in adjacent regions. The set of cluster variables, $Cl_{li,2006}$, $l = 1, 2, \dots, m$, employed here covers cluster strength (specialization) and diversity, which are further discussed in Sect. 5.2. The spatial lags $SL(Cl_{li,2006})$ are defined with the aid of spatial weights w_{ir} as

$$SL(Cl_{li,2006}) = \sum_{r=1}^n w_{ir} \cdot Cl_{ri,2006} \quad (2)$$

with n being the number of sample regions (in our case, $n = 402$). We make use of the contiguity concept to define row-standardized spatial weights w_{ir} (Arbia, 2006, pp. 37–38). Row-standardization is obtained by dividing the original binary weights w_{ir}^* ,

$$w_{ir}^* = \begin{cases} 1 & \text{if } i \text{ and } r \text{ are neighbours} \\ 0 & \text{otherwise} \end{cases}$$

by the sum $\sum_r w_{ir}^*$. In Equation (1), a set of additional regressors is included particularly to control for regional characteristics that influence regional productivity growth other than cluster effects. For instance, it may involve employment-related variables of experience, qualification, gender and sectoral disaggregation. Furthermore, a dummy variable for time-fixed effects can be included. The error component, α_i , captures unobserved regional heterogeneity; $u_{i,2003+4 \cdot h}$ is a remainder idiosyncratic error component.

To account for growth as a long-term phenomenon, the growth rate of productivity is computed for four 5-year periods (Islam, 1995).³ Specifically, productivity growth is measured for the intervals 2003–2007, 2007–2011, 2011–2015 and 2015–2019. Initial productivity and the regional characteristics are established in the starting years 2003, 2007, 2011 and 2015 for each 5-year period. The cluster variables, $Cl_{li,2006}$, are measured for the mid-point year 2006 of the period of investigation. Although cluster structures are not invariant over time, changes are more likely expected to occur slowly than in a spontaneous fashion (Menzel & Fornahl, 2010). We thus follow Delgado et al. (2014) who base their evaluation of cluster effects on given industry clusters for a period of 16 years.

Diverse cluster effects on the regional performance are measured through the regression coefficients γ and γ^* . While γ measures the impact of a region's own clustering activities on its productivity growth, γ^* denotes the spatial spillover parameter. Competitive advantages from productivity gains arising from own region's sectoral clusters (in R&D-intensive industries) entail a positive cluster coefficient γ . If industry clusters in surrounding areas contribute to improving regional performance, the spillover coefficient γ^* will take a positive value as well. Cluster benefits may coincide with a convergence or divergence of regions (Delgado et al., 2014). Here a differentiation between absolute and conditional convergence comes into play. As region-specific variables are included in (1), the coefficient of initial productivity, δ , provides a measure of conditional regional convergence. A negative value of the convergence parameter δ indicates that regions converge to their own steady states. Finally, the regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ measure the influences of the observed control variables x_1, x_2, \dots, x_k on regional productivity growth.

Convergence models are originally derived from neoclassical growth theory with regard to income per capita and labor productivity (Barro & Sala i Martin, 2003). Particularly with a view on the diffusion of new technologies, it becomes evident that the phenomenon of convergence is also inherently connected with the process of innovation (cf. Andergassen et al., 2017; Veugelers, 2017). Innovation growth is closely related to the available stock of knowledge, which is created by different firms or research institutions. While Archibugi and Filippetti (2010) make use of the convergence equation to study innovation dynamics across EU countries, Delgado et al. (2014) investigate cluster impacts on industry-specific patenting growth in the presence of innovation convergence.

In view of the potential presence of a heterogeneity bias, we base the econometric estimation of cluster effects on the within-between random effect (REWB) formulation of the correlated random effects (CRE) approach (see Appendix II). Within this framework, the panel data model

$$\log\left(\frac{y_{i,2003+4 \cdot h}}{y_{i,2003+4 \cdot (h-1)}}\right) = \alpha_0 + \delta \cdot \log(y_{i,2003+4 \cdot (h-1)}) + \sum_{l=1}^m \gamma_l \cdot Cl_{li,2006} + \sum_{l=1}^m \gamma_l^* \cdot SL(Cl_{li,2006}) + \sum_{j=1}^k \beta_{jW} \cdot (x_{ji,2003+4 \cdot (h-1)} - \bar{x}_{ji}) + \sum_{j=1}^k \beta_{jB} \cdot \bar{x}_{ji} + \alpha_i + u_{i,2003+4 \cdot h} \quad (3)$$

is obtained as are-parametrization of the Mundlak model. Whereas the regression coefficients $\beta_{1W}, \beta_{2W}, \dots, \beta_{kW}$ of the deviations ($x_{jit} - \bar{x}_{ji}$) measure the within effects, the regression coefficients $\beta_{1B}, \beta_{2B}, \dots, \beta_{kB}$ of the means \bar{x}_{ji} reflect the between effects.

Despite the consideration of the correlation of the unobserved and observed regional characteristics, Equation (3) can yet not be consistently estimated. This is because the log of the initial productivity level enters into the calculation of productivity growth as outcome variable and thus correlates with the disturbance terms. This correlation between $y_{i,2003+4 \cdot (h-1)}$ and u_{ih} introduces a simultaneity that give rise for an endogeneity bias in the convergence model specifications.

To account for the endogeneity bias within the CRE approach, we make use of the random effects instrumental variables (REIV) estimator with special regard to initial productivity and the knowledge stock (Wooldridge, 2010, pp. 349–353). Initial productivity is instrumented by its historical pre-sample values coupled with the actual number of inhabitants and population density. Consequently, not only the regressors but also the now instrumented initial level variables $y_{i,2003+4 \cdot (h-1)}$ uncorrelated with the idiosyncratic disturbance term $u_{i,2003+4 \cdot h}$. As for the regional characteristics, regional means of the latter variables are introduced in the final convergence model to capture potential correlation with unobserved heterogeneity.

4 | CLUSTER IDENTIFICATION

The econometric analysis of cluster effects on regional competitiveness builds on the identification of regional clusters in R&D-intensive industries in Germany (Kosfeld & Titze, 2017). Technology-focused cluster with strong R&D activities can be seen as a particular group of industrial clusters associated with high regional growth potentials through technology transfer into the region, new firm formation, and spin-offs (John & Pouder, 2006).

While firms in all industrial sectors spend a part of their revenue on R&D, four two-digit industries account for roughly two-thirds of nearly 52 billion Euros private R&D expenditure in Germany, namely the automotive industry with a share of approximately one-third, the electrical industry with a share of 20%, the chemical industry with a share of 17%, and the mechanical engineering industry with a share of 9%. At a higher degree of sectoral disaggregation (NACE Rev. 1.1), eight two- and three-digit R&D-intensive industries can be identified for the case of Germany. These eight sectors overlap with the group of high- or medium-high-technology manufacturing industries and high-tech knowledge intensive service industries according to Eurostat's classification of high-tech industries and knowledge intensive services.⁴ Based on the German input-output table for the year 2006 (Federal Statistical Office of Germany, 2010), dominant intermediate flows between these key R&D-intensive and related sectors are identified with the aid of qualitative input-output analysis (Kosfeld & Titze, 2017; Titze et al., 2011). The qualitative and quantitative compositions of the value-added chains form the national cluster templates (Table 1).

Based on this classification of Germany's R&D-intensive industries, regional clusters in these industries are computed using employment data at the level of NUTS-3 regions. Employment data are provided by the German Federal Employment Office. The NUTS-3 level covers 402 urban and rural districts that vary considerably in size and economic power. The employment statistics of the German Federal Employment Office provides the deepest subdivision of Germany for which sectoral employment data is available. The numbers of employees subject to social security contributions are available for the given 71 sectors of the Statistical Classification of Economic Activities in the European Community (NACE Version 1.1).

In identifying potential regional clusters typically spatial methods are employed that preferably rely on cluster indices capturing dimensions such as specialization, size and focus (cf. Sternberg &

TABLE 1 Cluster templates for German R&D intensive industries.

Key sectors	Related sectors
Automotive cluster (34)	25.2, 28, 31.
Chemical cluster (24 \ 24.4)	17, 19, 20, 21.2, 22.2–22.3, 24.4, 25.1, 25.2, 26.1, 26.2–26.8, 27.4, 27.5, 36
Pharmaceutical cluster (24.4)	24 \ 24.4
Machinery and equipment cluster (29)	25.1, 25.2, 26.1, 26.2–26.8, 27.1–27.3, 27.5, 28, 31, 35, 36
IT cluster (30 and 72)	28, 64, 73
Electrical machinery and apparatus clusters (31)	28, 29, 33, 34, 35
Radio, television, communication equipment and apparatus clusters (32)	28
Medical, precision and optical instruments clusters (33)	25.2, 28, 31

Note: Sector codes are based on the Classification of Economic Activities NACE Rev. 1.1 (Commission Regulation (EC) No 29/2002). Benchmark value-added chains identified by qualitative input-output analysis are taken from Kosfeld and Titze (2017). A description of the related sectors is listed in Table A1 of the appendix.

Litzenberger, 2004; European Commission 2011). However, by treating regions as isolated economies, these methods disregard all forms of spatial interaction. Furthermore, they are typically characterized by a purely descriptive orientation.

One exception is Brenner (2006) who adopts a probabilistic approach to identify local clusters by analyzing the spatial distribution of firms. The author applies a likelihood ratio test to check whether the empirical distribution shows an adequate fit to a Boltzmann-like distribution representing the 'cluster distribution'. While the approach is flexible with respect to the threshold of absolute and relative numbers of firms or employees, the cluster identification is difficult at least in two aspects. First, local clusters are identified for industries separately. Interactions with related industries are ignored. Secondly, the reach of industry clusters is restricted to the boundaries of administrative districts.

Various types of spatial methods aim at overcoming the restriction of isolated regions in identifying regional clusters. By accounting for local spatial association, the search procedures explicitly capture cluster activity across regional boundaries (cf. Feser et al., 2005; Pires et al., 2013). While Feser et al. (2005) implements the Getis-Ord G_i^* test for a first-order geographical neighborhood, Pires et al. (2013) define adjacency by the concept of k -nearest neighbours. Instead of fixing the spatial neighborhood in advance, adjacency can alternatively be defined by a predetermined distance. Although not developed for searches within varying regional surroundings, local Moran or Getis-Ord G_i^* tests (Aldstadt, 2010; Getis, 2010) could, in principle, be carried out for a series of spatial weights matrices. However, such a procedure would come along with a considerable loss of power when applied to a large number of multiple comparisons (Kosfeld & Titze, 2017).

In our approach, the identification of regional clusters of R&D-intensive industries is achieved in a multistage process (Kosfeld & Titze, 2017). First, national cluster templates in the form of value-added chains of R&D core industries and related industries are constructed as shown in Table 1. Based on direct and indirect linkages in the national input-output (I-O) table, we then use techniques of qualitative input-output analysis (QIOA) to establish substantial interindustry relationships. Secondly, regional production activity within these value-added chains is appraised on the basis of district employment data with the aid of national Leontief coefficients. Thirdly, the localization of potential industry clusters is examined using spatial scanning. Finally, those clusters with a critical mass of a geographical concentration of interconnected companies (measured by employment data) are identified as Porterian-type clusters.

We take especially advantage of Kulldorff's spatial scan method (Kulldorff, 1997; Kulldorff & Nagarwalla, 1995) as a search procedure for determining the cluster boundaries automatically by accounting for spatial externalities. The spatial scan test for potential clusters in a study area is based on a likelihood ratio approach. The method is especially devised for detecting clusters of varying sizes by correctly addressing the multiple testing problem (Aldstadt, 2010). Likelihood ratio statistics are computed for usually irregular shaped zones that are defined by circular windows around the centroids of each region up to a maximal size. For each spatial unit the likelihood ratio is maximized. The zones with the highest score values associated with each spatial unit are the most significant potential cluster areas. The procedure is particularly appealing when industry clusters exist with different spatial scales.

However, not all detected potential cluster areas with significant employment in R&D-intensive industries form a cluster according to Porter's cluster theory. Porterian-type clusters are characterized by three main features:

- size,
- focus,
- specialization.

These criteria are usually implemented using common thresholds.⁵ The size criterion stresses the role of a critical mass of a geographical concentration of interconnected companies taking a key position in an economic sector (Feser et al., 2005; Menzel & Fornahl, 2010; Porter, 1998, 2000). We account for this criterion by adopting a threshold of 100 employees in the core industry for the minimum cluster size. Cluster districts with a lower number of employees in the core industry are not viewed as a constituent part of a regional cluster. The focus criterion involves the relation of cluster and total employment in a region (cf. Feser et al., 2005; Sternberg & Litzenger, 2004; European Commission 2011). Here we use a share of 10% as a threshold for the focus criterion. The specialization criterion is usually related to the location quotient (for a definition see next section). In order to belong to a cluster, this indicator must exceed the value 1 in a region (cf. Sternberg & Litzenger, 2004; European Commission 2011).

5 | DATA AND MEASUREMENT

5.1 | Regional data

For the identification of regional clusters in R&D-intensive industries and the assessment of their impact on regional competitiveness, we employ various data sources. National cluster templates (see Table 1) are formed with the aid of the German input-output table for 2006 coupled with the corresponding evaluation tables (Federal Statistical Office of Germany, 2010). The input-output table consists of 71 sectors at the two- and, in part, three-digit sectoral level according to the classification of products by activity (CPA). Because it is the aim here to identify regional production linkages, imports are excluded from the analysis. The year 2006 was chosen for comparative purposes with regard to traditional cluster mapping approaches (Kosfeld & Titze, 2017).

As regional input-output tables only exist in exceptional cases, regional value-added chains are produced by linking the national benchmarks with sectoral employment data. For this endeavour, the employment statistics of the German Federal Employment Office is used that provides the deepest subdivision of Germany for which sectoral employment data is available. This allows us to identify cluster boundaries at the NUTS-3 level. The NUTS-3 level covers 402 urban and rural districts that vary in size and economic power.⁶ At this level of geographical disaggregation, data on the number of

TABLE 2 Descriptive statistics.

Variable	Min	Q1	median	mean	Q3	max
Prodpe	34.53	50.57	56.79	58.44	63.51	141.65
g (Prodpe)	-0.182	0.052	0.082	0.085	0.115	0.634
LQ	0.000	0.128	0.687	0.903	1.257	6.526
LQ (Auto)	0.000	0.000	0.000	0.335	0.000	4.842
LQ (Chem)	0.000	0.000	0.000	0.855	0.000	32.694
LQ (Pharma)	0.000	0.000	0.000	0.515	0.000	9.696
LQ (Mach)	0.000	0.000	0.000	1.176	2.023	11.307
H	0.000	0.000	0.178	0.426	0.764	1.778
nCl	0.000	1.000	1.000	1.751	3.000	7.000
J	0.000	0.000	0.257	0.417	0.879	1.000
Young empl	0.148	0.207	0.221	0.223	0.239	0.313
Old empl	0.153	0.223	0.261	0.266	0.306	0.429
Qualified empl	0.031	0.072	0.093	0.104	0.121	0.324
Industry share	0.019	0.183	0.250	0.261	0.336	0.682
Services share	0.154	0.331	0.389	0.399	0.450	0.747
Agriculture	0.000	0.004	0.009	0.014	0.018	0.116
Firm size	6.50	10.50	12.20	13.05	14.90	52.40

Note: Prodpe: Labour productivity (GDP per employees), g(Prodpe): 5-year growth rate of GDP/E, LQ: Cluster specific location quotient (9), H: Shannon's entropy (11), nCl: Number of R&D clusters, J: Pie-lous's evenness (12), Young empl: Share of employees younger than 30 years, Old empl: Share of employees of 50 years or older, Qualified empl: Share of high qualified workers (acad. degree), Industry share: Share of employees in industry sector, Services share: Share of employees in service sector, Agriculture share: Share of employees in agriculture sector, Firm size: Average number of employees per firm in full-time equivalents.

employees subject to social security contributions is available for the given 71 sectors of the Statistical classification of economic activities in the European Community (NACE Vers. 1.1). This largest group of the working population accounts to almost three fourth of total employment. Both classifications, CPA and NACE, are linked as they share the same conceptual framework.

Sectoral employment data at the NUTS-3 level is also used to compute various facets of clustering that are included as various cluster variables in the convergence regressions outlined above.⁷ Specifically, we define (1) cluster strength (specialization) and (2) cluster diversity as general measures of agglomeration economies within cluster regions. Additionally, we make use of (2a) cluster variety and (2b) cluster balance as the main constituents of the cluster diversity measure. To ascertain to which types of R&D-intensive clusters potential agglomeration effects can be attributed, cluster-specific location quotients based on employment data are calculated.

Descriptive statistics of the variables considered for the empirical analysis of cluster effects are provided in Table 2. Labor productivity is defined as gross regional product (GRP) per employee. GRP data and total regional employment are obtained from the working group "National Accounts of the Federal States". Growth rates of regional productivity are used as the key outcome variables of interest linked to the notion of regional competitiveness. They are calculated for the four 5-year periods 2003–2007, 2007–2011, 2011–2015 and 2015–2019. Convergence is assessed from the coefficients of the initial levels of labor productivity and patent stock at the start of both 5-year periods.

When we identify the impact of R&D-intensive clusters on productivity growth, we control for a broad set of regional characteristics. This intends to minimize the risk of introducing an omitted

variable bias into our convergence models. In view of a presumed link between productivity and wages, individual characteristics like vocational education, experience and gender should be included in the productivity growth model (cf. Heckman et al., 2003). Thus, we account for the shares of young and elder workers, the shares of high and low-qualified workers and the share of employed females at the regional level. In addition, the relative magnitude of the manufacturing and service sector as well as average firm size may influence productivity dynamics. Data on the control variables is provided at the NUTS-3 level by the German Federal Employment Agency. Inasmuch the regional characteristics are not sufficient to cover the East German productivity gap (Ragnitz, 2007), a supplementary spatial control has to be made to capture the East-West divide.

The spatial distributions of labor productivity and its growth rates along with two selected cluster measures are exhibited in Figure 1. Regions with high labor productivity are notably located in South Germany and some parts of West and North Germany (Panel A of Figure 1). In East Germany, high productivity regions are only found by exception. However, high growth regions are not only located in South Germany but especially also in East Germany (Panel B of Figure 1). On the one hand, productivity growth seems to be driven by cluster strength (Panel C and D of Figure 1). On the other hand, a catching-up process may be a source of upward pressure on productivity. This makes it necessary to link the nexus between productivity growth and industrial clusters to regional convergence.

5.2 | Cluster measures

In Porter's cluster concept, specialization and agglomeration of related and supporting industries are seen as drivers of productivity growth (Porter, 2008, pp. 192–194, 263). This view shifts the focus from industry specialization to cluster specialization in assessing competitive advantages of regions. The measurement of cluster strength (i.e., specialization) usually draws on the method of location quotients (LQs). To ascertain effects from individual clusters, cluster-specific location quotients are defined. Although cluster strength can also be thought of in absolute terms (cf. Maine et al., 2010), most researcher hereby understand the relative presence of a group of related industries in an area relative to their presence in the overall economy (cf. Delgado et al., 2014; Resbeut & Gugler, 2016; Slaper et al., 2018). As to that, typically variations of the location quotient (LQ) are employed. The location quotient is widely used to assess industrial specialization and clustering (cf. Crawley et al., 2013; O'Donoghue & Gleave, 2004; Tian, 2013).

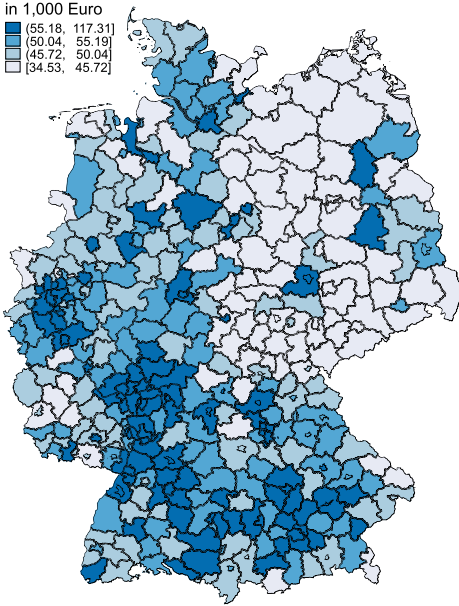
Aiginger and Davies (2004) define specialization of a (national) economy by a high share of production activity in a small number of industries. At the regional scale, the focus shifts to identifying relative specialization. High activity shares of few industries in one area relative to the national shares will show up in a large LQ measure that indicates regional specialization.

Cluster-specific location coefficients can be self-contained employed to establish from which R&D-intensive clusters substantial agglomeration effects originate. By aggregating cluster-specific LQ measures they provide the strength of cluster specialization of a region can be measured (cf. Delgado et al., 2014; Slaper et al., 2018). For reasons of data availability, we use employment data for quantifying economic activity. The cluster-specific location quotients $LQ_{i,cl}$ then result from a comparison of the shares of cluster-specific and total employment in the individual areas and the entire economy:

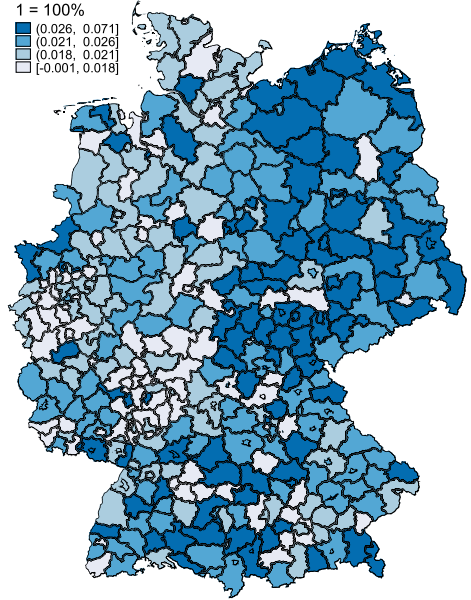
$$LQ_{i,cl} = \frac{e_{i,cl}/e_i}{E_{cl}/E} = \frac{e_{i,cl}/E_{cl}}{e_i/E}, \quad cl = 1, 2, \dots, nCl_i \quad (4)$$

While $e_{i,cl}$ is employment of cluster cl in region i and e_i total employment in region i , E_{cl} is the national cluster employment and E the total national employment. nCl_i is the number of R&D-intensive clusters in area i . The cluster-specific LQs reflect the extent of specialization of regional value-added chains.

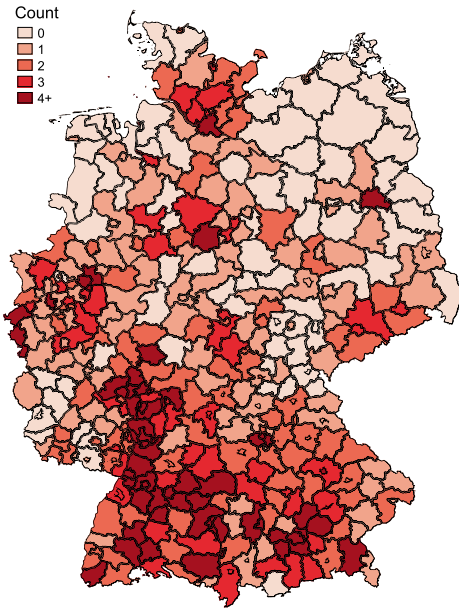
A: Labour productivity in 2003



B: Annual productivity growth 2003-2019



C: Number of R&D intensive clusters



D: Cluster-based location quotient (LQ)

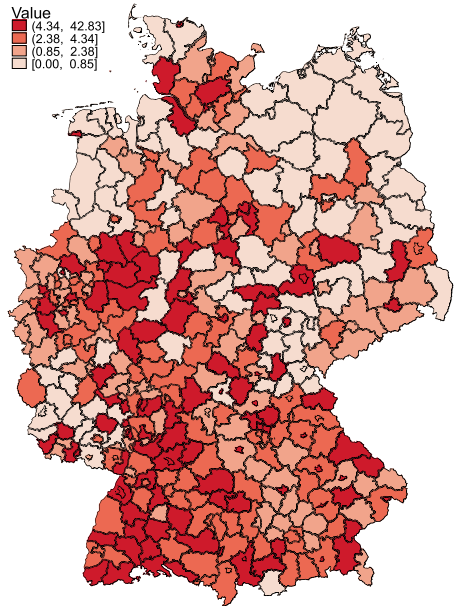


FIGURE 1 Spatial distributions of labor productivity, growth rates, and R&D clusters. Panels A, B and D show quartiles of the distribution of variables.

TABLE 3 Frequency distribution of the regional number of R&D-intensive clusters.

Number of R&D clusters	0	1	2	3	4	5	6	7
Frequency	84	115	95	51	42	13	1	1

To determine the extent of cluster specialization in a region, we sum all cluster-specific-locations quotients of the region and divide them by the number of clusters in that region. That is, we use the average of the cluster specific location quotients $LQ_{i,cl}$:

$$\overline{LQ}_i = \frac{1}{nCl_i} \sum_{cl=1}^{nCl_i} LQ_{i,cl} \quad (5)$$

As a measure of cluster strength. The relative concentration of employment in R&D-intensive clusters is expected to vary considerably across regions.

High specialization may make regions vulnerable to ups and downs of special industries. Economic shocks are better absorbed by industrial diversification as the decline in one sector can be offset by the growth in another sector (Slaper et al., 2018). Feser et al. (2014) especially addresses a region's vulnerability to a particular cluster. On the one hand, economic resiliency of regions can be fostered by cluster diversity. On the other hand, the competitiveness of regions can be advanced by productivity gains arising from important innovations that stem from a recombination of knowledge from diverse value-added chains (cf. Frenken et al., 2007). Whereas industries within a cluster are linked through the notion of related variety, different clusters are coupled with unrelated variety (Slaper et al., 2018).⁸

Diversity is used as a performance measure in different disciplines (Stirling, 2007). Interdisciplinary research on diversity puts forth comparative studies on different concepts of diversity. This also holds for agglomeration theory, where different approaches to industrial diversification are used. Well-established diversity measures are Shannon's entropy, the Simpson index and the Gini index (Jost, 2010; Leydesdorff, 2018; Stirling, 1998, 2007). Particularly because of its decomposition property, the Shannon index has raised the interest of economists and economic geographers for the study of economic sectors (cf. Frenken et al., 2007; Theil, 1972). Here we make use Shannon's entropy that is defined by

$$H_i = - \sum_{cl=1}^{nCl_i} p_{I,cl} \cdot \ln(p_{I,cl}) \quad (6)$$

with nCl as the total number of clusters in the whole area.⁹ The highest level of diversity is characterized by an equal distribution of cluster activity in the region under consideration. In this case, H_i reaches its upper bound $\ln(nCl_i)$ with nCl_i as the number of clusters in the i th region. The lowest level of diversity is obtained when all cluster activities are concentrated in one field. This state is linked with the minimum entropy bound of zero.

Cluster diversity can be decomposed into a variety and balance indicator. Although it reaches its maximum value for equal cluster shares, the H index is not a pure measure of balance. Shannon's entropy is not only affected by the pattern of employment shares but additionally by variety. For establishing the balance of regional cluster patterns with Shannon-type measure, the variety effect has to be identified and eliminated. Variety signifies the richness of system elements with respect to the phenomenon under analysis. It is commonly operationalized by the number of types in which the entities are apportioned. Here variety is measured by the number of clusters of R&D-intensive industries present in a region (nCl_i). Table 3 shows the distribution of the number of clusters in German NUTS

3 regions that determine the variety index. As the table shows, a large number of regions do not host any R&D cluster. Another striking feature from Table 3 is that regions with R&D-intensive clusters typically only host a limited number of clusters, while regions with multiple clusters (>5) are the exception.

The log of the variety index is identical with the maximum possible cluster diversity in the considered region. We additionally define dummy variables capturing the number of regional clusters in order to obtain supplementary information on specialization versus diversity effects.

Balance refers to the evenness of the distribution amongst the categories. A region is perfectly balanced when the cluster types are evenly distributed. Thus, balance is a function of the regional proportions of economic activity in the cluster field. Pielous's evenness J_i aims at removing the variety effect from Shannon's entropy by dividing the diversity measure by the log of the number of regional clusters nCl_i (Jost, 2010; Stirling, 1998, 2007).¹⁰

$$J_i = H_i / \ln(nCl_i) \quad (7)$$

According to Jost (2010), J is a particularly well-behaved measure of evenness. The interdisciplinary literature identifies disparity as a third component of diversity (Leydesdorff, 2018; Stirling, 1998, 2007). Disparity relates to the question how distinct the categories—here the cluster types—are from each other. However, the disparity dimension is often assumed to be predetermined by the classification scheme. On that account, we make use of the ‘dual concept’ of diversity consisting of the dimensions balance and variety.

6 | ESTIMATION RESULTS

Table 4 presents the benchmark estimation results to quantify the link between regional clusters and productivity in German NUTS-3 regions. From the cluster-theoretical point of view, productivity growth is a key reflection of competitiveness of regions and nations (Camagni, 2002; Martin et al., 2006; Porter, 1998, 2000, 2009). First and foremost, general cluster impacts are traced in the interplay between dispersion and agglomeration forces. According to the above discussion, impacts from cluster specialization and diversity are distinguished. After focusing on a region's own opportunities from clustering of economic activity, the relevance of spatial cluster spillovers for productivity dynamics is examined. Eventually, we wish to obtain insight into the extent of cluster specialization and on the nature of specific cluster effects.

The estimation results reveal that convergence is accompanied by significant cluster effects for several specifications of the productivity growth model (Table 4). Labor productivity is instrumented by using the last four lagged productivity variables as well as population and density as instruments. Their high correlation with the initial labor productivity qualifies them as good instruments. According to the Hansen-Sargan J test exogeneity of instruments is ensured in all cases. The co-existence of agglomeration effects and convergence dynamics is particularly well interpretable when regions do not converge to the same but to their own long-run productivity levels. Here, conditional convergence follows from the relevance of regional characteristics for the convergence process. The estimated speed of convergence amounts to 3.7% per annum. As distinguished from Delgado et al. (2014), concomitance of convergence and agglomeration here occurs within the same spatial units. The highly significant Wald statistic shows that the explanatory variables jointly explain regionally varying productivity growth rates.

The positive impact of cluster strength on regional productivity is robust and highly statistically significant in all baseline model specifications. This indicates that regions with specialized

TABLE 4 Convergence and cluster impacts on productivity growth (Baseline models).

	BM I	BM II	BM III	BM IV	BM V	BM VI
Initial productivity	-0.1651** (0.0190)	-0.1529** (0.0192)	-0.1617** (0.0195)	-0.1546** (0.0194)	-0.1525** (0.0189)	-0.1614** (0.0195)
Cluster strength	0.0093** (0.0026)		0.0106** (0.0031)			0.0109** (0.0032)
Cluster diversity		0.0007 (0.0036)	-0.0050 (0.0043)			
Cluster variety				0.0008 (0.0013)		-0.0016 (0.0022)
Cluster balance					0.0004 (0.0042)	-0.0012 (0.0062)
Controls	2x7	2x7	2x7	2x7	2x7	2x7
RE	Region	Region	Region	Region	Region	Region
DF	1591	1591	1590	1591	1591	1589
Wald	193.9**	192.6**	200.5**	191.6**	190.1**	202.9**
Pseudo- R^2	0.1291	0.1214	0.1300	0.1215	0.1214	0.1301
R inst	$t = 1: 0.966$	$t = 2: 0.989$		$t = 3: 0.986$		$t = 4: 0.982$
pJ	0.4217	0.6416	0.3828	0.6540	0.6468	0.4487

Note: Period of investigation: 2003–2019, Number of spatial units (n): 402, Number of 5-year periods (T): 4; Heteroscedasticity-consistent (HC) standard errors in parenthesis, ** 1% significance level, * 5% significance level (*) 10% significance level, RE: Random effects, DF: Degrees of freedom, Wald: Chi-square test of slope coefficients being jointly zero, Pseudo R^2 : R squared of pseudo differenced data; R inst: Correlation between initial productivity and instrumented productivity, pJ : p -values from Hansen-Sargan J test of overidentifying restrictions.

R&D-intensive clusters tend to experience higher productivity growth rates than non-clustered areas. On the other hand, cluster diversity does not seem to bring about beneficial effects for productivity dynamics. Neither isolated nor in conjunction with the indicator of relative specialization does the diversity mechanism show any significant effects at standard critical levels. This also holds when cluster diversity is decomposed in its constituent parts variety and balance.

With regard to productivity growth, our findings on the effects of R&D-intensive clusters are well in line with those of Slaper et al. (2018) for traded clusters across US metropolitan areas. For this type of cluster, a positive and significant cluster strength effect and a non-significant evenness effect is identified. However, as the authors only consider the balance component of diversity, no results are provided for variety and overall diversity of cluster structures. While not explicitly focusing on productivity performance, Maine et al. (2010) ascertained significant strength and diversity effects on growth of new technology-based firms in separate regressions. Once the distance to the largest cluster is included in the regression, all diversity-based indicators lose their statistical significance.

A number of observed regional characteristics are considered as control variables (see Panel A of Table A2). As their effects are very similar in the different specifications of the productivity model, we focus on model BM I where all statistically nonsignificant cluster measures are left out. The directions of the impacts can be interpreted in a meaningful way for all control variables. The nonsignificant effect of young workers and significant negative effect of old workers imply that high productivity growth comes along with a large share of workers in the middle age group. A rise in the share of skilled workers is associated with a highly significant increase of productivity growth. With respect to the sectoral breakdown, the expected effects are measured. Presumably productivity growth is

TABLE 5 Convergence, cluster impacts and spatial effects on productivity growth (Spatial models).

	SM I	SM II	SM III	SM IV	SM V	SM VI
Initial productivity	-0.1675** (0.0199)	-0.1582** (0.0204)	-0.1651** (0.0205)	-0.1595** (0.0204)	-0.1554** (0.0198)	-0.1665** (0.0205)
Cluster strength	0.0090** (0.0027)		0.0103** (0.0031)			0.0113** (0.0033)
SL (Cluster strength)	0.0021 (0.0027)		0.0025 (0.0031)			0.0001 (0.0035)
Cluster diversity		-0.0014 (0.0039)	-0.0063 (0.0043)			
SL (Cluster diversity)		0.0085 (0.0057)	0.0021 (0.0068)			
Cluster variety				-0.0002 (0.0014)		-0.0028 (0.0022)
SL (Cluster variety)				0.0030 (0.0019)		0.0070 (0.0045)
Cluster balance					-0.0009 (0.0046)	-0.0003 (0.0064)
SL (Cluster balance)					0.0060 (0.0070)	-0.0166 (0.0142)
Controls	2x7	2x7	2x7	2x7	2x7	2x7
RE	Region	Region	Region	Region	Region	Region
DF	1590	1590	1588	1590	1590	1586
Wald	185.8**	192.6**	201.2**	191.6**	190.3**	204.8**
Pseudo-R ²	0.1294	0.1227	0.1308	0.1229	0.1219	0.1322
R inst	$t = 1: 0.966$	$t = 2: 0.989$	$t = 3: 0.986$	$t = 4: 0.982$		
pJ	0.3895	0.6626	0.3741	0.6746	0.7115	0.2793
p (rw)	0.60	0.56	0.58	0.56	0.56	0.56

Note: Period of investigation: 2003–2019, Number of spatial units (n): 402, Number of 5-year periods (T): 4, Heteroscedasticity-consistent (HC) standard errors in parenthesis, ** 1% significance level, * 5% significance level (*) 10% significance level, RE: Random effects, DF: Degrees of freedom, Wald: Chi-square test of slope coefficients being jointly zero, Pseudo R²: R squared of pseudo differenced data, R inst: Correlation between initial productivity and instrumented productivity, pJ: Hansen-Sargan J test of overidentifying restrictions, p(rw): Randomization-based test of spatial dependence for panel models.

negatively affected by a high regional share of the service sector activity because productivity gains are limited in public, household or social security services. This applies even stronger for regions with a larger share of agriculture. Both sector effects are measured relative to the impact of the industrial sector. Eventually, there is some evidence that productivity growth is a positive function of firm size. All effects of the control variables are robust across different specifications of the productivity model.

Productivity growth effects may additionally originate from cluster specialization in neighbouring regions (Table 5). They could specifically occur in small-scale areas on the grounds of regional interaction. Yet, spatial autocorrelation is already accounted for in delineating regional clusters by the spatial scan test. The identified clusters most often spread over surrounding districts (Kosfeld & Titze, 2017). On that account only spatial effects of productivity growth not already captured by spatial autocorrelation of employment will be shown up in the empirical convergence model. The estimation results reported in Table 5 give no indication on the existence of such supplementary spillover

TABLE 6 Degree of specialization and specific cluster specialization (productivity).

A. Degree of specialization		B. Specific cluster specialization	
Initial productivity	-0.1744** (0.0627)	Initial productivity	-0.1730** (0.0626)
1 cluster	0.0079(*) (0.0047)	LQ (AutoCl)	0.0035* (0.0016)
2 clusters	0.0016 (0.0053)	LQ (ChemistryCl)	0.0010(*) (0.0006)
3 clusters	0.0218** (0.0065)	LQ (PharmaCl)	0.0011(*) (0.0007)
4 clusters	0.0073 (0.0064)	LQ (MachineCl)	0.0045* (0.0020)
>4 clusters	0.0011 (0.0076)		
Controls	Yes	Controls	Yes
RE	Region	RE	Region
Wald	166.7**	Wald	139.4**
Pseudo- R^2	0.0751	Pseudo- R^2	0.0537

Note: Heteroscedasticity-consistent (HC) standard errors in parenthesis, ** 1% significance level, * 5% significance level (*) 10% significance level, WALD: Chi-square test of slope coefficients being jointly zero, Pseudo R^2 : R squared of pseudo differenced data, Partial R^2 and F: Partial R-squared and F statistic of first stage regression (instrumenting initial productivity).

effects. Thus, virtually all potential spatial spillovers of productivity growth are already captured in delimiting the geographical range of R&D-intensive clusters. The effects of the control variables are robust in all spatial models (see Panel B of Table A2).

In all cases, the cluster strength effect turns out to be highly statistically significant. As statistical significance depends on the sample size (Hangartner & Gill, 2011; Royal, 1986), this finding needs some qualifications. As in the case of our large sample, statistical significance is easier to prove than in small samples,¹¹ hence, the meaning of the significance test arises. In large samples already a small magnitude of difference may lead to a highly statistically significant effect. While statistical significance is concerned with the sampling variability, practical significance is related to the size of the effect (Mohajeri et al., 2021). In our case the effect size of cluster strength on productivity growth is about 1% point given an average growth rate of 8.5% in the four 5-year periods. Thus, the high statistical significance of cluster specialization comes along with high a practical significance by 12% raise of productivity growth in specialized clustered areas.

The findings provide strong evidence that specialized clustered areas (cluster specialization) may be able to reap competitive advantages in the form of stronger productivity growth. Because of non-significant regression coefficients of all measures related to cluster diversity, productivity gains do not come from a large number of clusters.¹² Indeed, a strength-based effect can arise from regional specialization in only one or a few clusters (Panel A of Table 6). This result links to region-specific case studies that investigate the potential effects of cross-cluster collaboration (Bathelt & Zhao, 2020).

Finally, we wish to know with which types of R&D-intensive clusters productivity growth effects from regional specialization are associated. In their study on growth effects of new technology-based firms, Maine, Shapiro and Vining (2008) find beneficial diversity effects in the domains of IT and communication equipment. Similarly, Brave and Mattoon (2020) find that business services and other knowledge-based industries are of importance for the underlying cluster strength of the local economy. In our case, especially advantages from cluster specialization in automobile production and machinery are disclosed (Panel B of Table 6). With some qualifications this also holds for the production of chemical and pharmaceutical products. Different from findings for the U.S., our results thus point to the role of key sectors in Germany's industrial model. Both estimation results are supportive for Marshallian externalities in productivity dynamics. Jacobs-type spillovers tend to be at least partially

realized whenever the cluster strength effect does not only originate from one but a few clusters in a region.

7 | CONCLUSIONS

Strong regional clusters with highly competitive local firms are increasingly seen as a local response to economic globalization by policy makers and regional development agencies. Because of the presumed connection between clustering and high productivity growth as a measure for regional competitiveness, the cluster approach has become very appealing in different fields of economic policy. However, up to now, there is scarce empirical evidence for the impact of clustering on regional competitiveness from quantitative research studies. To some extent, the issue of regional competitiveness has been addressed in econometric studies on cluster impacts on regional performance (Spencer et al., 2010; Delgado et al., 2014; Slaper et al., 2018; Ketels & Protsiv, 2021). In their investigation of cluster effects on firm growth, Maine et al. (2010) are additionally delving into the benefits of specific clusters.

In extension to the above literature, we have provided a comprehensive analysis of the different mechanisms that may lead to differences in productivity growth in regions without or with one or even multiple R&D-intensive clusters. Besides the effect of cluster strength, we have also looked at the potential role played by cluster diversity in a region. Using a spatial panel data approach, we were able to control for observable regional characteristics and unobserved regional heterogeneity. Whereas spatial autocorrelation is already regarded in delineating regional clusters, spatial cluster spillovers are additionally taken into account in the modeling framework.

For Germany, we partially find significant positive cluster effects on regional competitiveness in the presence of conditional convergence. It is not cluster diversity that matters for productivity growth but cluster strength. The impact of cluster specialization on productivity growth is already measured at level of NUTS-3 regions. The lack of neighboring effects may, on the one hand, be due to the fact that spatial spillovers are already captured in cluster identification. On the other, our results provide further evidence that the benefits from cooperation and knowledge sharing within clusters are highly localized.

No effect could be ascertained for higher levels of cluster diversity. This also applies for cluster variety and balance as constituents. However, this does not necessarily imply that regional competitiveness is influenced solely by MAR- or Porter externalities. The sectoral composition of clusters always incorporates related variety to some degree. Jacobs-type externalities may be at least partially present when the strength effect does not only originate from one but a few clusters. With respect to productivity growth, it appears that the regional growth performance is positively affected by the endowment of a region with up to 3 R&D-intensive clusters in different technological fields. Specific cluster effects on productivity growth emanate from the production of automotives, chemical and pharmaceutical products and machine construction.

With regard to policy recommendations, our results clearly show that cluster-based regional development approaches need to be implemented carefully as not all types of clustering activities translate into higher productivity and innovation growth. While cluster strength is in general associated with higher productivity growth, reality has proven that it could be difficult to copy successful examples of strong clusters in alternative regional context conditions (Hospers et al., 2008). However, in the presence of regional productivity convergence, cluster specialization can be a beneficial strategy to foster the catching-up process of lagging areas. In addition to the general role played by cluster strength, our results also point to the fact that positive productivity effects from

clustering are mainly the result of the interplay of a limited number of R&D-intensive clusters in the region and confine to certain sectors such as the automotive industry and the machinery sector. These sectoral patterns show that regional R&D clusters are a strong backbone of Germany's industrial model.

Given that the cluster concept chosen here accounts for underlying input-output relationships along a common technology value chain, our results also lend support to the current practice of Science and Technology (S&T) policy, which supports strong cluster initiative that cross sectoral and technological boundaries. This may be important to avoid lock-in effects of strong mono-industrial clusters and to foster continuous structural change in the economy. An example for such a policy is the current setup of Germany's leading edge cluster competition (Rothgang et al., 2015). Thus, policy makers should not only view clusters as a development strategy in small local business communities but also take into account the potential of positive growth externalities to the broader spatial environment when designing future cluster policy schemes.

Future research should particularly focus on the joined space-time determination of regional clusters and competitiveness indicators such as productivity growth in order to better identify the causal mechanisms at play in this complex relationship. With the limited time dimension at hand, our research had to start from the underlying assumption that a given (exogenous) cluster landscape in Germany unfolds its effects on regional competitiveness. With the help of longer time series data, future analysis should relax this assumption to better understand how strong clusters evolve and how these clusters then impact regional competitiveness. However, until such data are available, we hope that our empirical results can be used meaningfully in the ongoing debate about the role of clusters and cluster policy for regional growth and development.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

- ¹ In newer studies, cluster specialization and cluster strength are used as synonyms (s. Delgado et al., 2014, 2016; Slaper et al., 2018).
- ² This is in particular expected in persistent clusters. Yet the issue of competitive advantages of clustering is closely linked to the notion of cluster life cycles or, more general, cluster evolution. See, for example, Menzel and Fornahl (2010) and Martin and Sunley (2011).
- ³ Although it would be feasible to use time spans as short as 1 year, neglecting growth as a long-term phenomenon would entail detrimental consequences. In particular, larger disturbances, a stronger propensity to error autocorrelation and a greater dependence by business cycle fluctuations is expected with short time intervals (Islam, 1995). In his study on growth empirics, Islam (1995) shows the advantageousness of a panel analysis based on 5-year sub-periods.

- ⁴ For details, see https://ec.europa.eu/eurostat/cache/metadata/EN/htec_esms.htm.
- ⁵ Brenner (2006) points to potential deficiencies of applying fixed threshold levels in the literature of cluster identification. His use of flexible thresholds is, however, restricted to his parametric approach of a cluster distribution.
- ⁶ Originally, regional R&D-intensive clusters are defined for 439 German districts (Kosfeld & Titze, 2017). To account for data revisions and local government reforms in East Germany, we use the updated employment data of 402 NUTS-3 regions following the territorial changes.
- ⁷ The concepts and definitions of the cluster variables are presented in the second part of this section (sub-section 5.2).
- ⁸ Depending on the cluster definition, clusters can overlap to different degrees (Delgado et al., 2014; Feser et al., 2014). According to our specific definition of clusters from national templates of value-added chains, the regional clusters used here are highly diverse.
- ⁹ For $p_{i,cl} = 0$ the terms $0 \cdot \ln(0)$ is set equal to 0 according to its limit $\lim_{p_{i,cl} \rightarrow 0^+} p_{i,cl} \cdot \ln(p_{i,cl}) = 0$.
- ¹⁰ Jost (2010) shows that evenness and variety components of diversity are not independent of each other, so that the variety effect can only partially be removed.
- ¹¹ Furthermore, the type II error of accepting the null hypothesis of no productivity effect when the alternative hypothesis is true is reduced with increasing sample size (Hangartner & Gill, 2011).
- ¹² Cluster specialization and diversity effects are robust to the different choice of time periods 2001–2006 and 2006–2011.
- ¹³ Technically, the FE estimator results from pooled OLS estimation of the time-demeaned model, while the RE estimator is obtained from a pooled OLS regression of the quasi-time-demeaned variables (cf. Wooldridge, 2010, pp. 327).
- ¹⁴ The conditional mean independence assumption (A2) is necessary to fully justify statistical inference in the RE model (cf. Wooldridge, 2010, p. 286).

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APPENDIX

I | Within-between random effect (REWB) variant of the CRE approach

From a traditional econometric point of view, a standard approach would be to estimate the growth model in Equations (1) and (3) by means of a fixed-effects model in the case of a lack of a sampling scheme for the spatial units (Elhorst, 2014, pp. 55–56). However, standard fixed-effects (FE) estimation is not feasible here, as the cluster variables enter the growth equations as time-invariant regressors. This means that in the case of FE estimation no cluster impacts can be identified since cluster variables are eliminated by the within transformation (cf. Kelejian & Piras, 2017; Krishnakumar, 2006, p. 322). In contrast, with a random effects (RE) specification of the unobservables, impacts of the time-invariant cluster variables are still identifiable. Despite the stated traditional view, the use of random effects approaches is well established in spatial econometrics (cf. Baltagi et al., 2013; Debarsy, 2012; Kelejian & Piras, 2017, p. 308).

A modern econometric view relates the difference between the fixed effects (FE) and random effects (RE) model to the correlation between the observed explanatory variables x_1, x_2, \dots, x_k and the unobserved regional effect α_i (Wooldridge, 2010, p. 286).¹³ While the FE model allows a correlation between both type of variables,

$$\text{Cov}(\alpha_i, \mathbf{x}_{i1}) = \text{Cov}(\alpha_i, \mathbf{x}_{i2}) \neq 0 \quad (\text{A1})$$

for consistent estimation, RE estimates of the regression coefficients would become inconsistent. Thus, the principal obstacle for the RE estimation of a growth model such as in Equations (1) and (3) in the current form is the potential correlation between the unobserved effects α_i and the explanatory variables x_1, x_2, \dots, x_k . This is usually the case when unobserved regional heterogeneity, induced, for instance, by different local amenities and institutional settings, is related to observed regional characteristics like the shares of highly educated people, young workers and the sectoral structure.

To consistently estimate the panel data model, we draw on the correlated random effects (CRE) approach as a unifying fixed and random effects scheme (Wooldridge, 2010, pp. 286–290). In order to remove the heterogeneity bias, the correlated random effects (CRE) approach introduces individual heterogeneity into the estimation model. This is done by replacing the assumption of a constant conditional expectation of unobserved regional effects,¹⁴

$$E(\alpha_i | \mathbf{x}_{i1}, \mathbf{x}_{i2}) = \alpha_0, \quad (\text{A2})$$

by the premise of a conditional expectation depending on the regional means $\bar{x}_{1i}, \bar{x}_{2i}, \dots, \bar{x}_{ki}$ of the observables:

$$E(\alpha_i | \mathbf{x}_{i1}, \mathbf{x}_{i2}) = E(\alpha_i | \bar{\mathbf{x}}_i) = \alpha_0 + \sum_{j=1}^k \beta_{jC} \cdot \bar{x}_{ji} \quad (\text{A3})$$

(cf. Wooldridge, 2010, pp. 287–288; Miranda et al., 2017). The $k \times 1$ vectors \mathbf{x}_{i1} and \mathbf{x}_{i2} contain the initial values of the x -variables for region i in the first and second period, respectively. $\bar{\mathbf{x}}_i$ is a $k \times 1$ vector of regional means over time. α_0 is a constant and $\beta_{1C}, \beta_{2C}, \dots, \beta_{kC}$ are “contextual effects” that capture the difference between the within and between effect (cf. Bell et al., 2019; Bell & Jones, 2015). With the individual error $\eta_i = \alpha_i - E(\alpha_i | \mathbf{x}_{i1}, \mathbf{x}_{i2})$, the Mundlak variant of the CRE approach specifies regional heterogeneity α_i by

$$\alpha_i = \alpha_0 + \sum_{j=1}^k \beta_{jC} \cdot \bar{x}_{ji} + \eta_i \quad (\text{A4})$$

Under the precondition (A1), the heterogeneity bias is removed, and the zero conditional expectation assumption of the form (A3) holds for the unobserved random effects η_i . While the set of regional characteristics is uncorrelated with η_i , they will be correlated with their regional means. The correlation will also disappear when the deviations of the x -variables from their means instead of their levels enter the panel data model. This is done in the within-between random effect (REWB) formulation that partitions the influence of the x variables into a within and between effect (cf. Bell et al., 2019; Bell & Jones, 2015).

II | Additional Tables

TABLE A1 R&D intensive industries and their related sectors.

Code	Sector
17	Manufacture of textiles
19	Manufacture of leather and leather products
20	Manufacture of wood and wood products
21.1	Manufacture of pulp, paper and paperboard
21.2	Manufacture of articles of paper and paperboard
22.2–22.3	Printing and service activities related to printing; reproduction of recorded media
24\24.4	Manufacture of chemicals and chemical products
24.4	Manufacture of pharmaceuticals, medical chemicals and botanical products
25.1	Manufacture of rubber products
25.2	Manufacture of plastic products
26.1	Manufacture of glass and glass products
26\26.1	Manufacture of other non-metallic mineral products without glass and glass products
27.1	Manufacture of basic iron and steel and of ferro-alloys;
27.3	Manufacture of tubes; other first processing of iron and steel
27.4	Manufacture of basic precious and non-ferrous metals
27.5	Casting of metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus n.e.c.

TABLE A 1 (Continued)

Code	Sector
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture; manufacturing n.e.c.
72	Computer and related service activities
73	Research and development services

Source: Classification of Economic Activities NACE Rev. 1.1 (Commission Regulation (EC) No 29/2002).

TABLE A 2 Influence of control variables on productivity growth.

Model BMI	Within	Between
Young empl	-0.0617 (0.2339)	-0.0801 (0.1300)
Old empl	0.2148* (0.1082)	-0.3210 ^(*) (0.1668)
Qualified empl	0.1191 (0.2557)	0.2105** (0.0631)
Industry share	-0.1405 (0.1271)	-0.0326 (0.0385)
Services share	-0.4348** (0.1169)	-0.1279* (0.0547)
Agriculture	-1.4068* (0.5939)	0.3136 ^(*) (0.1729)
Firm size	0.0514 (0.0784)	0.0024 ^(*) (0.0013)
Model SMI	Within	Between
Young empl	-0.0614 (0.2338)	-0.1029 (0.1344)
Old empl	0.2182* (0.1086)	-0.3351* (0.1697)
Qualified empl	0.1199 (0.2557)	0.2041** (0.0619)
Industry share	-0.1395 (0.1271)	-0.0349 (0.0385)
Services share	-0.4343** (0.1169)	-0.1274* (0.0548)
Agriculture	-1.4074* (0.5966)	0.3306 ^(*) (0.1709)
Firm size	0.0523 (0.0784)	0.0025* (0.0013)

Note: Heteroscedasticity-consistent (HC) standard errors in parenthesis, ** 1% significance level, * 5% significance level ^(*) 10% significance level.