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The role of R&D-intensive clusters for 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 and innovation growth. In analogy to the industry-oriented concepts of related and unrelated variety (Frenken, Van Oort, Verburg 2007), we differentiate between effects of cluster specialisation and diversity. The identification of R&D-intensive clusters is based on a hybrid approach of qualitative input-output analysis and spatial scanning (Kosfeld and Titze 2017). Our empirical study is conducted for a panel of German NUTS-3 regions in 2001-2011. To comprehensive account for specialisation and diversity effects of clustering we adopt a spatial econometric approach, which allows us to identify these effects beyond the geographical boundaries of a single region. 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 a limited number of R&D-intensive clusters in specific technological fields is most strongly linked to higher levels of regional productivity growth. While we also observe a positive effect of cluster strength on innovation growth once we account for spatial spillovers, no significant effects of 'cluster diversity' can be identified. This indicates that some but not all cluster-based regional development strategies are promising policy tools to foster regional growth processes.

Key words:
Industry clusters, regional competitiveness, cluster specialisation, cluster diversity, correlated random effects model

JEL: L16, R11, R15

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1. Introduction

Spatial clustering of economic activity is a worldwide phenomenon that has attracted an unabated interest among academics and policmakers - fuelled by seminal research contributions of influential scholars like Michael Porter (1990) and Paul Krugman (1991). 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 (Njøs and Jakobsen 2016; Slaper, Harmon and Rubin 2018; Spencer et al. 2010).

While cluster policy in highly developed areas primarily aim at strenghtening 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 practises that could inspire regional planning agencies and decison makers in other industrial environments. While qualitative case studies typically provide a detailed description of cluster actors and their interaction (Schmiedeberg, 2010), they are typically incapable of proving favourable effects from cluster support activities.

Quantitative research on the impact of clustering on economic activity primarily focusses on investigating the role played by agglomeration economies on the structural performance of firms or regions (Slaper, Harmon and Rubin 2018). Although the different strands of the evaluation literature have to cope with the common problem of adequately identiying 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 large 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 network structure and evolution of clusters, which are often at the heart of the qualitative case study approach.

A plethora of case studies have been conducted to gain insights on the contributions of initiatives, networking and support measures for the efficiency of individual clusters. Likewise a large variety of investigations on external effects from agglomeration of economic activity exist. However, only scarce evidence is available on agglomeration effects resulting from the co-location of actors in closely related industries, i.e. clusters. Without controlling for regional characteristics, statistical analyses, as for instance correlation analysis, bear the danger of drawing erronous conclusions on cluster effects

(Spencer et al. 2010). Therefore the adoption of a proper econometric modelling approach is indicated. In explicitly relying on existing cluster theories, an identification of regional clusters is required as necessary prerequiste of the empirical identification strategy.

In the last decade, some research papers have started to use an 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 (Census Metropolitan Areas and Census Agglomerations) and assess their effects on regional performance. Delgado, Porter and Stern (2014) have developed a convergence model to evaluate cluster effects on employment and patenting growth at the region-industry level. Most recently, Slaper, Harmon and Rubin (2018) have investigated the strength of cluster effects on regional performance in the United States.

However, up to now, a comprehensive evaluation of cluster impacts on regional competitiveness in the presence of opposing convergence forces is still missing. 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 highlighted in recent studies (Alexiadis 2013, pp. 141; Dîrzu 2013, Guastella and Timpano 2016; Sonn and Park 2011). Whereas Delgado, Porter and Stern (2014) have investigated the importance of cluster effects for job creation and innovation of regional industries in the presence of convergence, virtually no knowledge is available about the role of industry clusters on the economic performance of regions in this interplay. Uncovering cluster impacts on regional competition under the occurrence of both conflicting forces thus remains an open task.

In contrast to most other studies, Delgado, Porter and Stern (2014) take explicitly account of spillovers from clusters in surrounding regions. While the studies of Maine, Shapiro and Vining (2008) and Slaper, Harmon and Rubin (2018) aim to disclose effects of both cluster strength and cluster diversity, Delgado, Porter and Stern (2014) focus on ascertaining the impacts of cluster specialisation and related clusters on performance measures. The former effects give special insight into the relevance of Marshall-Arrow-Romer (MAR) externalities and Jabobs-type externalities from the perspective of clusters. They can be sensibly discussed in connection with the concepts of related and unrelated variety introduced by Frenken, Van Oort and Verburg (2007).

By adopting a spatial econometric approach, we allow for region-specific effects and cross-regional spillovers stemming from both type of clustering structures on regional competition. In accordance with cluster theory we assume that competitive advantages will show up in productivity and innovation growth (Porter 1990, 1998, 2000, 2003;

Cingano and Schivardi 2004; Cortright 2006; Delgado, Porter and Stern 2010). The present study thus aims at assessing the impacts of 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 and innovation growth (cf. Porter 1990, 1998, 2000, 2003; Cingano and Schivardi 2004; Cortright 2006; Delgado, Porter and Stern 2010).

Without cluster effects, lagging areas may catch up to highly productive or innovative regions. However, in the field of tension between convergence and agglomeration forces, on the one hand, advanced regions can keep or extend their initial advantage. On the other hand, backward regions with cluster effects can catch up faster or overtake higher developed regions. We add to this literature by dividing the potential agglomeration economies into the effects of cluster strength (specialisation) and diversity when taking account for convergence effects and spatial spillovers. In contrast to the above studies, spatial autocorrelation is also already considered in delineating regional industry clusters. By using a panel data approach, we control for both observable regional characteristics and unobserved regional heterogeneity.

The paper is structured as follows. After the introduction, in section 2 we focus on the theoretical foundations of agglomeration economies and clustering with respect to regional competition. Section 3 addresses the delineation of regional clusters of R&D-intensive industries. In section 4, the econometric modelling approach for identifying 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. Evidence of cluster impacts on innovation growth performance is discussed in section 7. The final section 8 concludes the paper and draws some policy implications.

2. Agglomeration theory and regional clusters

The theory of clusters is marked by different schools of thought embracing a variety of methodological approaches. Bibliometric analyses have started to organise these different strands, concepts and topics of research on industrial clusters in a comprehensive manner (Cruz and Teixeira 2010; Lazaretti, Sedita, and Caloffi 2014). Because economic clusters entail a geographical concentration of firms and workers, most aproaches originate from the field of location and agglomeration theory. In agglomerations, positive specialisation effects are attributable to internal and external economies of scale. Alfred Marshall (1920) devised positive externalities in the form of economies of localisation in an analysis of industrial organisation. Advantages of specialisation external to firms arise from pooling of specialised labour, proximity to suppliers and knowledge spillovers. Since the influential studies of Porter (1990, 1998, 2003), business scholars and economists have become aware of the idea that Marshallian agglomeration economies are more associated with regional clusters than only with local sectors. With view to a more rigorous theoretical foundation of industry-specific knowledge spillovers in follow-up research, agglomeration economies are referred to as Marshall-Arrow-Romer (MAR) externalities (Glaeser et al. 1992). Even if some restrictions may have to be taken into account, specialisation effects of MAR externalites are typically reasoned to advance productivity growth (de Lucio, Herce and Goicolea 2002; Dekle 2002; Henderson 2003; Cingano and Schivardi 2004; Almeida 2007; Frenken, van Oort and Verburg 2007).

Another type of externalities, which is advantageous for regional growth, can be found in sectoral diversity. Jacobs (1969) argued that externalities of a geographical concentration of a variety of industries arise from sharing access to a wider pool of qualified labour market and a diverse supply of intermediate goods. On top of that, Jacobs-type externalities include knowledge spillovers from diverse industries that may be more important than those within the same industry leaving out any complementary activites.[3] While intra-industry (MAR) knowledge spillovers especially give rise to incremental product innovation and process innovation, inter-industries (Jacobs-type) knowledge spillovers are expected to have the potential for bringing about major innovations (Fagerberg 2003; Nathan and Overman 2013). With the production of similar goods, spillovers tend to bring about gradual improvements that can enhance productivity growth. More radical innovations require recombination of knowledge on technologies and practises from diverse sectors. Frenken, van Oort and Verburg (2007) therefore argue that Jacobs externalites are especially strong with a related variety of sectors.

Porter’s cluster approach does not simply 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 (Porter 2000; Martin and Sunley 2003). In his influential contribution on the role of economic geography for global competition, Porter (2000) defines a cluster as a “geographically proximate group of interconnected companies and associated institutions in a particular field, 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

[3] Jacobs externalities are not always clearly distinguished from urbanisation economics. Originally the concept of urbanisation economies was associated with the size of a city not with its sectoral structure (Hoover 1948, pp. 120-121, 1999/1971, sect. 5.4.2; Henderson 1986). Later the notion shifts in some works to urban diversity that is also the reasoning behind Jacobs externalities (Glaeser et al. 1992; Henderson, Kuncoro and Turner 1995; Henderson 2003). Frenken, van Ooort and Verburg (2007) differentiate between externalities arising from urban size and densitiy (urbanisation economies) and a variety of sectors (Jacobs externalities). From the latter, however, unrelated variety is excluded because it is viewed as a means of portfolio diversication giving rise for urbanisation economies.

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.

With his diamond model, Porter (1990) has introduced an eclectic model for the role of clustering stressing that local competition is conductive for innovation and growth (see also Porter 1998, 2000; Almeida, 2007; Glaeser et al. 1992; Runiewicz-Wardyn 2013). In contrast to MAR models (cf. Romer 1986), the market structure of Porter's diamond model is not monopolistic but stresses the role of competition. Thus, positive externalities in the diamond model arise from geographically concentrated core industries along with their related sectors endowed with highly competitive enterprises (Porter externalities). The diamond model claims that firms' competitive advantages are affected by the local business environments that are determined by four factors (Porter 1998, 2000): input factor 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. Innovation and productivity growth are believed to depend crucially on the quality of these mutually interdependent factors. A certain influence of government on factor conditions, e.g. on qualification and the regulatory environment, gives a rationale for cluster-based policies.

While MAR externalities rest upon monopolistic elements (Romer 1986), productivity and innovation gains in regional clusters are based on competitive behaviour. Porter externalities share the competitive market structure in common with Jacobs-type spillovers. As a cluster involves a group of firms from a core industry along with actors from related sectors, it is generally recognised that cluster specialisation[4] involves more than merely industrial specialisation effects. Already with view on the involvement of supply and demand relations, related sectors are more comprehensive than sugested by the literature on MAR externalities. Also horizontal linkages may be involved in regional clusters by technological commonalities. Thus, cluster specilisation partially covers Jacobs-type externalities that can be characterized as related variety by Franken, van Oort and Verburg (2007).

On this account, Njøs and Jakobsen (2016) ascribe agglomeration advantages emanating from related variety of industral clusters as the „middle ground" between Marshall–Arrow–Romer (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 acount for all interconnections between sectors. Delgado, Porter and Stern (2016) underline that different types of relatedness like knowledge links, input-output links, skill-based links, co-location patterns of industries or product similarity are used to define clusters of related industries.

[4] In newer studies, cluster specialisation and cluster strength are used as synonyms (s. Delgado, Porter and Stern 2014, 2016; Slaper, Harmon and Rubin 2018).

Regional clusters therefore always cover related variety to some degree. Although cluster diversity is closely connected to unrelated variety, both concepts are not congruent.

Focussing on the role of agglomeration economies in the working of cluster effects, the specific impact of cluster strength and cluster diversity on regional competitiveness and growth come into the focus of research. While cluster specialisation is reasoned to be the major driver of productivity growth through incremental innovations, cluster diversity is expected to provide an environment favourable for more radical innovations. However, beneficial cluster effects will likely be offset by certain types of agglomeration disadvantages - at least partially. Congestion, increased environmental pollution and transport costs represent countervailing, dispersive forces. Attached to initial levels of productivity and innovation, forces towards 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.[5]

Although the concept of clusters is strongly grounded in agglomeration theory, it also does involve elements of location, innovation and network theory (Vom Hofe and Chen 2006). Given this multidisciplinary view of clusters, a certain degree of vagueness in the concept of clusters has been highlighted by Martin and Sunley (2003). Yet, particularly in more recent studies there seems to be a growing agreement on four constituting elements of industrial clusters (cf. Feser and Bergman 2000; Feser, Sweeney, and Renski 2005; Feser, Rensky, and Koo 2009; Spencer et a. 2010; Titze, Brachert, and Kubis 2011; Slaper, Harmon and Rubin (2018). Firstly, a cluster consists of a group of firms operating in a core industry and its related sectors. Secondly, the actors belonging to a cluster are interconnected, i.e. they form part of a network.[6] Thirdly, the enterprises are proximate to each other, i.e. a cluster is a geographic concentration of firms. Fourth, a critical mass of actors is presumed for agglomeration economies to be effective.

3. Econometric modelling 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 methods are typically applied (e.g. Garone et al. 2012, 2016; Gertler et al. 2011; Giuliani et al. 2013). These methods are designed to assess the impact of a policy measure (or exogenous

[5] This is in particular expected in persistant clusters. Yet the issue of competitve advantages of clustering is closely linked to the notion of cluster life cycles or, more genrally, cluster evolution. See e.g. Menzel and Fornahl (2010) and Martin and Sunley (2011).

[6] However, for the existence of a cluster, firms need not necessarily be conscious of being part of a network of producers (Ketels, Lindqvist, and Sölvell 2006).

shock) by comparing the current situation after its implementation of the policy measure (shock) with the case that would have occurred in its absence. This counterfactual situation is constructed with the aid of information on the variables of interest in the pre-treatment period.

The situation is different when potential benefits of regional clusters are investigated (Delgado, Porter and Stern 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. Menzel and Fohrnal 2009; Fornahl and Hassing 2017). Once established, they persist over years until they may (potentially) completely disappear at the end of their maturity stage. As changes of cluster structures tend to increase over time, in this study, we narrow down (‘freeze’) the time frame to five years before and after the year of cluster identification.[7] By keeping a limited degree of temporal variation in the data structure, this principally offers the opportunity to use panel data models to account for unobserved regional characteristics and transregional trends in evaluating cluster effects.

Specifically, we adopt a spatial panel data approach to econometrically investigate the impacts of regional clusters of R&D intensive industrial core sectors on regional competitiveness. The simultaneous existence of opposite forces may be rationalized at the region-industry level (Delgado, Porter amd Stern 2014), but there is an extensive literature that substantiates convergence at the regional level (cf. Islam 1995; Sala-I-Martin 1996). Both economic forces may 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:

$$(1) \qquad \log\left(\frac{Prodpe_{i,2001+5\cdot h}}{Prodpe_{i,2001+5\cdot(h-1)}}\right) = \delta \cdot \log(Prodpe_{i,2001+5\cdot(h-1)}) + \sum_{l=1}^{m} \gamma_l \cdot Cl_{li,2006}$$
$$+ \sum_{l=1}^{m} \gamma_l^{*} \cdot SL(Cl_{li,2006}) + \sum_{j=1}^{k} \beta_j \cdot x_{ji,2001+5\cdot(h-1)} + \alpha_i + u_{i,h}$$

with i=1,2,… ,402 regions and h=1,2 periods. The convergence model (1) explains productivity growth in region i in the period 2001-2011, $\log\left(\frac{Prodpe_{i,2001+5\cdot h}}{Prodpe_{i,2001+5\cdot(h-1)}}\right)$, by its initial productivity level, $\log(Prodpe_{i,2001+5\cdot(h-1)})$, the presence of cluster effects

[7] Delgado, Porter and Stern (2014) assume a persistence of cluster structure over a period of sixteen years.

from the own region i, $CI_{li,2006}$, and spatial cluster effects $SL(CI_{li,2006})$ from cluster activities in adjacent regions . The set of cluster variables, $CI_{li,2006}$, l=1,2,…, m, employed here cover cluster strength (specialization) and diversity, which are discussed in Sect. 5.2. The spatial lags $SL(CI_{li,2006})$ are defined with the aid of spatial weights w_{ir}:

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

with n being the number of regions (n=402). Here we make use of the contiguity concept to define row-standardised spatial weights w_{il} (Arbia 2006, p. 37-38). They are obtained by dividing the original binary weights w_{ir}^*,

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

by the sum $\sum_r w_{ir}^*$. A set of additional regressors are included particularly to control for regional characteristics that influence productivity growth other then cluster effects. For instance, it may involve variables of experience, qualification, gender and sectoral disaggregation. Furthermore, a dummy variabe for time-fixed effects can be included. The quantity, α_i, capture unobserved regional heterogeneity. $u_{i,h}$ is an idiosyncratic disturbance variable.

To account for growth as a long-term phenomenon, the growth rate of productivity is computed for two 5-year periods (Islam 1995).[8] Specifically, productivity growth is measured for the intervals 2001 to 2006 and 2006 to 2011. Initial productivity and the regional characteristics are established in the starting years 2001 and 2006 for each 5-year period. The cluster variables, $CI_{li,2006}$, are measured for the mid-point year 2006 of the period of investigation. Although cluster structrures are not invariant over time, changes are more likely expected to occur slowly than in an erratic fashion (Menzel and Fornahl 2009). Whereas Delgado, Porter and Stern (2014) base their evaluation of cluster effects on given industry clusters for a period of 16 years, we assume cluster stabiltiy for a 10 year interval around the year of cluster identification.

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

[8] Although it would be feasible to use time spans as short as one 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 five year sub-periods.

activities on its productivity growth, γ^* denotes the spatial spillover parameter. Competitive advantages from productivity gains arising from own region's industry clusters entail a positive cluster coeffient γ. If industry clusters in surrounding areas contribute to improving regional performance, the spillover coefficent γ^* will take a positive value as well. Cluster benefits may coincide with a convergence or divergence of regions (Delago, Porter and Stern 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 coeffients β_1, β_2, …, β_k measure the influences of the observed control variables x_1, x_2, …, x_k on regional productivity growth.

Convergence models are originally derived from neoclassical growth theory with regard to income per capita and labour productivity (Barro and 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, Nardini and Ricottilli 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, Porter and Stern (2014) investigate cluster impacts on industry-specific patenting growth in the presence of innovation convergence.

In analogy to our productivity growth model, we pursue the convergence approach in studying cluster effects on innovation growth:

$$(3) \qquad \log\left(\frac{Innov_{i,2001+5\cdot h}}{Innov_{i,2001+5\cdot(h-1)}}\right) = \delta\cdot\log(Innov_{i,2001+5\cdot(h-1)}) + \sum_{l=1}^{m}\gamma_l\cdot CI_{li,2006}$$
$$+\sum_{l=1}^{m}\gamma_l^*\cdot SL(CI_{li,2006}) + \sum_{j=1}^{k}\beta_j\cdot x_{ji,2001+5\cdot(h-1)} + \alpha_i + u_{i,h}$$

with i=1,2,… ,402 regions and h=1,2 periods. In equation (3), innovation growth in region i during the period 2001-2011, $\log\left(\frac{Innov_{i,2001+5\cdot h}}{Innov_{i,2001+5\cdot(h-1)}}\right)$, is explained by the initial stock of knowledge, $\log(Innov_{i,2001+5\cdot(h-1)})$, the presence of cluster effects from the own region i, $CI_{li,2006}$, spatial cluster effects $SL(CI_{li,2006})$ and observable regional characteristics $x_{ji,2001+5\cdot(h-1)}$. As in the model for productivity growth, we account for the presence of unobserved regional heterogeneity through the inclusion of α_i. Unsystematic influences are captured by the disturbance variable u.

Following the identification of general cluster impacts, we also seek to find out the most advantageous degree of specialisation. For this endeavour, dummy variables for the presence of one, two, three, four and more than four regional clusters are introduced into the convergence model. Subsequently, we test the relevance of specific RD-invensive cluster types on regional competitiveness by using sector-specific location quotients. In this way, R&D-intensive clusters shall be identified that substantially contribute to productivity and innovation growth across German regions.

From a traditional econometric point of view, a standard approach would be to estimate the growth model (1) and (3) by means of as a fixed-effects model in the case of a lack of a sampling scheme for the spatial units (Elhorst 2014, p. 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 tranformation (cf. Krishnakumar 2006; Kelejian and Piras 2017, 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, Egger and Pfaffermayr 2013; Debarsy 2012; Kelejian and Piras 2017, pp. 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, …, x_k and the unobserved regional effect α_i (Wooldridge 2010, p. 286).[9] While the FE model allows a correlation between both type of variables,

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

for consistent estimation, RE estimates of the regression coeffiencts would become inconsistent. Thus, the principal obstacle for the RE estimation of a growth model such as (1) and (3) in the current forms is the potential correlation between the unobserved effects α_i and the explanatory variables x_1, x_2, …, 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, p. 286-290). In order to remove the heterogeneity bias, the correlated random effects (CRE) approach introduces individual heterogeneity into the estimation model.

[9] 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)

This is done by replacing the assumption of a constant conditional expectation of unobserved regional effects,

(5) $\quad E(\alpha_i \mid \mathbf{x}_{i1}, \mathbf{x}_{i2}) = \alpha_0$,[10]

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

$$(6) \qquad E(\alpha_i \mid \mathbf{x}_{i1}, \mathbf{x}_{i2}) = E(\alpha_i \mid \bar{\mathbf{x}}_i) = \alpha_0 + \sum_{j=1}^{k} \beta_{jC} \cdot \bar{x}_{ji}$$

(cf. Wooldridge 2010, 287-288; Miranda, Martínez-Ibañez and Manjón-Antolín 2017). The kx1 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 kx1 vector of regional means over time. α_0 is a constant and $\beta_{1C}, \beta_{2C}, ..., \beta_{kC}$ are „contextual effects“ that capture the difference between the within and between effect (cf. Bell and Jones 2015; Bell, Fairbrother and Jones 2019). With the individual error $\eta_i = \alpha_i - E(\alpha_i \mid \mathbf{x}_{i1}, \mathbf{x}_{i2})$, the Mundlak variant of the CRE approach specifies regional heterogeneity α_i by

$$(7) \qquad \alpha_i = \alpha_0 + \sum_{j=1}^{k} \beta_{jC} \cdot \bar{x}_{ji} + \eta_i \, .$$

Under the precondition (4), the heterogeneity bias is removed and the zero conditional expectation assumption of the form (3) 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 and Jones 2015; Bell, Fairbrother and Jones 2019). The panel data model of the REWB variant of the CRE approach,

$$\begin{aligned} \log\left(\frac{y_{i,2001+5\cdot h}}{y_{i,2001+5\cdot(h-1)}}\right) &= \alpha_0 + \delta \cdot \log(y_{i,2001+5\cdot(h-1)}) + \sum_{l=1}^{m} \gamma_l \cdot CI_{li,2006} + \sum_{l=1}^{m} \gamma_l^* \cdot SL(CI_{li,2006}) \\ (8) \qquad &+ \sum_{j=1}^{k} \beta_{jW} \cdot (x_{ji,2001+5\cdot(h-1)} - \bar{x}_{ji}) + \sum_{j=1}^{k} \beta_{jB} \cdot \bar{x}_{ji} + \alpha_i + u_{ih} \, , \end{aligned}$$

for productivity growth ($y^{(1)}$=Prodpe) and innovation growth ($y^{(2)}$=Innov) is obtained by a reparametrization of the Mundlak framework. Whereas the regression regression

[10] The conditional mean independence assumption (5) that is stronger than assumption (4) is necessary to fully justify statistical inference in the RE model (cf. Wooldridge 2010, p. 286).

coefficients $\beta_{1W}, \beta_{2W}, ..., \beta_{kW}$ of the deviations $x_{jit} - \bar{x}_{ij}$ measure the within effects, the regression coeffients $\beta_{1B}, \beta_{2B}, ..., \beta_{kB}$ of the the means $\bar{x}_{ji}$ reflect the between effects.

Despite the consideration of the correlation of the unobserved and observed regional characteristics, (8) can yet not be consistently estimated. This is because the log of the initial productivity level and knowledge stocks are part of the respective dependent variable and thus correlated with the disturbance terms. This correlation between $y_{i,2001+5\cdot(h-1)}$ 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, p. 349-353). Initial productivity is instrumented by its historical value in the year prior to the sample period coupled with the actual number of inhabitants and population density. For instrumenting the initial state of knowledge, we construct knowledge stocks for the years 1996 and 1998 that do not overlap with the stocks used to measure the growth rate of innovation in the subsequent estimation periods. Consequently, not only the regressors but also the employed initial level variables $y_{i,2001+5\cdot(h-1)}$ are uncorrelated with the idiosyncratic disturbance term u_{ih}. 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 competiveness builds on the identification of regional clusters in R&D-intensive industries in Germany (Kosfeld and Titze 2017). 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 percent, the chemical industry with a share of 17 percent, and the mechanical engineering industry with a share of 9 percent. At lower levels of sectoral disaggregation, eight R&D-intensive industries can be distinguished. Based on the German input-ouput 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 (Titze, Brachert and Kubis 2011; Kosfeld and Titze 2017). The qualitative and quantitative compositions of the value-added chains form the national cluster templates (Table 1).

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: 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.

To identify potential regional clusters in R&D-intensive industries, employment data is used provided by the German Federal Employment Office at the level of NUTS-3 regions. 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 are available. The number of employees subject to social security contributions is available for the given seventy-one sectors of the Statistical classification of economic activities in the European Community (NACE Version 1.1).

In identifying potential regional clusters typically aspatial methods are employed that preferably rely on cluster indices capturing dimensions such as specialization, size and focus (cf. Sternberg and Litzenberger 2004; European Commission 2011). However, by treating regions as ‘closed’ economies, these methods disregard all forms of spatial interaction. Furthermore, they are typically characterized by a purely descriptive orientation. With the aid local spatial methods the restriction of isolated regions in the search for regional clusters can be overcome, though. By accounting for local spatial association, the search procedures explicitly capture cluster activity across regional boundaries (cf. Feser, Sweeney and Renski 2005; Pires et al. 2013). While Feser, Sweeney, and Renski (2005) implements the Getis-Ord Gi* test for a first-order geographical neighbourhood, Pires et al. (2013) define adjacency by the concept of k-nearest neighbours. Instead of fixing the spatial neighbourhood 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 Gi* tests (Getis 2010; Aldstadt 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 and Titze 2017).

Here we take advantage of Kulldorff's spatial scan method (Kulldorff and Nagarwalla 1995; Kulldorff 1997) as a search procedure for determining the cluster size automatically. More particularly, the spatial scan method is devised for detecting clusters of varying size by correctly addressing the multiple testing problem (Aldstadt 2010). The spatial scan for potential clusters in a study area is a testing approach that is based on a likelihood ratio approach. 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 clusters. As no closed-form distribution of the test statistics is known, the randomization testing approach is used in assessing statistical significance of most likely clusters.

In many cases, a variety of potential clusters is detected by spatial scanning regional systems with a large number of regional units (Kosfeld and Titze 2017). In such applications not all possible clusters may be of substantive interest. Using employment data, clustering in coherent territories reflects the focus of production activities in a specific field in the regions concerned. Statistically significant industry clusters originally detected by the spatial scan method may lack a critical mass for externalities (Menzel and Fornahl 2010). Porter (1998, 2000) stresses the role of a critical mass of a geographical concentration of interconnected companies taking a key position in an economic sector. Therefore the importance of a value-added chain in a region is determined by both dimensions focus and size (Feser, Sweeney and Renski 2005). The size criterion is taken into account by adopting a threshold for the minimum cluster size. Cluster districts with scarce employment in the core industry (< 100 employees) are not viewed as a constituent part of a regional cluster.

5. Data and measurement

5.1 Regional data

For identifying regional clusters of R&D-intensive industries and assessing their impact on regional competitiveness, we make recourse on various data sources. National cluster templates (s. 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 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 and 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.[11] At this level of geographical disaggregation, data on the number of 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.[12] 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.

Growth rates of regional productivity and innovation activities are used as the key outcome variables of interest linked to the notion of regional competitiveness. They are calculated for the two 5-year periods 2001 - 2006 and 2006 - 2011. We use regional patent applications at the European Patent Office (EPO) as proxy for regional innovation activities. Data have been retrieved from the OECD RegPat database (Maraut et al., 2008). Patent applications are geo-referenced by the inventor's place of residence and can thus be linked to NUTS-3 regions. We use fractional counting to distribute cases with multiple inventors of a patent application across these regions.[13] Convergence is assessed from the coefficents of the initial levels of labour productivity and

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[11] Origninally, regional R&D-intensive clusters are defined for 439 German districts (Kosfeld and 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.

[12] The concepts and definitions of the cluster variables are presented in the second part of this section (sub-section 5.2).

[13] Fractional counting divides a patent application with more than one inventor equally among all of them and subsequently among their regions. It thus avoids a double counting of patent applications.

patent stock at the start of both 5-year periods. While labour productivity is defined as gross regional product (GRP) per employee, the patent stock is obtained from patent applications through the perpetual inventory method.[14] GRP data and total regional employment are obtained from the working group "National Accounts of the Federal States“.

When we identify the impact of R&D-intensive clusters on productivity and innovation 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, Lochner and Todd 2003). Thus, we account for the shares of young and elder workers, the shares of high and low-qualiied 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. The control variables are also used to eliminate structural effects on innovation growth. 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.

5.2 Cluster measures

Here we define cluster strength (i.e. specialization) and diversity used to capture general cluster effects. While the strength indicator draws on the concept of the location quotient, the diversity measure makes use of Shannon’s entropy function. As constituents of cluster diversity, variety and balance indicators are considered. 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, Shapiro and Vining 2008), 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, Porter and Stern 2014; Resbeut and Gugler 2016; Slaper, Harmon and Rubin 2018). As to that, typically variations of the location quotient (LQ) are employed. The location

[14] The perpetual inventory method calculates the regional patent stock for a given sample period *t* on the basis of its previous year value (*t-1*), a fixed depreciation rate (δ) for knowledge capital and the number of patent applications in period *t* as $\mathrm{PATSTOCK_{i,t}} = (1 - \delta)\mathrm{PATSTOCK_{i,t-1}} + \mathrm{PATENT_{i,t}}$, where we follow the suggestion of O’Mahony et al. (2008) to set $\delta = 0.13$. Initial capital stocks are calculated as the sum of patent applications in three subsequent periods divided by the sum of the average growth rate of patent applications (φ) in the sample period 1995-2011 ($\varphi = 0.04$) and the above depreciation rate (δ) as $PATSTOCK_{i,0} = \sum_m^M PATENT_{i,0-m} / (\varphi + \delta)$, such that for *m*=0,1,2 we can calculate the initial patent stock for the period 2011 on the basis of patent applications in the period 1999-2001. Auxiliary patent stocks for the years 1996 and 1998 are similarly calculated on the basis of patent applications in 1995/1996 and 1997/1998, respectively. As outlined in the main text, these auxiliary patent stocks are used to instrument the included patent stocks for 2001 and 2006 in the growth model specifications.

quotient is widely used to asess industral specialization and clustering (cf. O'Donoqhue and Gleave 2004; Crawley, Beynon and Munday 2013; Tian 2013).

Aiginger and Davies (2004) define specialisation 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 specialisation. 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 specialisation. For determining the extent of cluster specialisation, Slaper, Harmon and Rubin (2018) make use of the average of the cluster specific location quotients,

$$(9)\quad \overline{LQ_i} = \frac{1}{nCl_i} \sum_{cl=1}^{nCl_i} LQ_{i,cl},$$

with the cluster specific LQ measures defined as

$$(10)\quad LQ_{i,cl} = \frac{e_{i,cl}/e_i}{E_{cl}/E} = \frac{e_{i,cl}/E_{cl}}{e_i/E},\ cl=1,2,\ \ldots,\ nCl_i.$$

The cluster-specific location quotients $LQ_{i,cl}$ result from a comparison of the shares of cluster-specific and total employment in the individual areas and the entire economy. For reasons of data availability, economic activity of R&D-intensive clusters is measured by employment. 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 $LQ_{i,cl}$ measures are addtionally individually employed to establish from which R&D-intensive clusters substantial agglomeration effects originate.

Diversity is used as a performance measure in different disciplines (Stirling 2007). Regional decision-makers often pursue the strategy of diversification to avoid or lessen the dependence on a single industry with the aim to decrease the vulnerabiltiy of a region to economic shocks and increase its resilience. Franken, Van Oort and Verburg (2007) hereby associate the notion of unrelated variety that is applied to a diverse of highly aggregated industries. The issue of vulnerabiltiy is also discussed with respect to a set of clusters knowing that they can overlap to different degrees depending on the exact cluster definition (Delgado et al. 2014; Feser et al. 2014). Whereas industries within a cluster are linked through the notion of related variety, between clusters is essentally only unrelated variety remaining (Slaper, Harmon and Rubin 2018).

In agglomeration theory and empirical regional research, different approaches to industrial diversification are used. Interdisciplinary research on diversity puts forth comparative studies on different concepts of diversity. Most often well-established diversity measures like Shannon's entropy, the Simpson index and the Gini index are the focus of interest (Stirling 1998, 2007; Jost 2010; Leydesdorff 2018). 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. Theil 1972; Frenken, Van Oort and Verburg 2007). First and foremost here we make use Shannon's entropy that is defined by

$$(11)\quad H_i = -\sum_{cl=1}^{nCl} p_{i,cl} \cdot \ln(p_{i,cl})$$

with nCl as the total number of clusters in the whole area.[15] The highest level of diversity is marked 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 present 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.

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 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 2 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.

Table 2: 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

The log of the variatey index is identical with the maximum possible cluster diversity in the considered region. We additionally define dummy variabes capturing the number of regional clusters in order to obain supplementary information on specialisation versus diversity effects.

Balance refers to the eveness 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

[15] For $p_{i,cl} = 0$ the terms $0 \cdot \ln(0)$ is set equl to 0 according to its limit $\lim_{p_{i,cl} \to 0+} p_{i,cl} \cdot \ln(p_{i,cl}) = 0$.

eveness 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 (Stirling 1998, 2007; Jost 2010):

(12) $J_i = H_i \,/\, \ln(nCl_i)$.[16]

According to Jost (2010) J is a particularly well-behaved measure of eveness. The interdisciplinary literature identifies disparity as a third component of diversity (Stirling 1998, 2007; Leydesdorff 2018). 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. Empirical results I: Clusters and productivity growth

In a first step, we econometrically investigate the impacts of regional clusters on productivity in German NUTS 3 regions. From the cluster-theoretic point of view, productivity growth is a key reflection of competitiveness of regions and nations (Camagni 2002; Martin, Kitson and Tyler 2006; Porter 1990, 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 specialisation and diversity are distinguished. After focussing on a region's own opportunities from clustering of economic actitivity, the relevance of spatial cluster spillovers for productivity dynamics is examined. Eventually, we wish to obtain insight into the extent of cluster specialisation and on the nature of specific cluster effects.

[16] Jost (2010) shows that eveness and variety components of diversity are not independent of each other, so that the variety effect can only partially be removed.

Table 3: Convergence and cluster impacts on productivity growth (Baseline models)

	BM I	BM II	BM III	BM IV	BM V	BM VI
Initial productivity	-0.1743** (0.0636)	-0.1744** (0.0636)	-0.1743** (0.0637)	-0.1744** (0.0636)	-0.1744** (0.0636)	-0.1743** (0.0638)
Cluster strength	0.0012* (0.0006)		0.0013* (0.0006)			0.0012* (0.0006)
Cluster diversity		0.0024 (0.0040)	0.0042 (0.0040)			
Cluster variety				0.0017 (0.0014)		0.0030 (0.0023)
Cluster balance					0.0018 (0.0047)	-0.0039 (0.0080)
Controls	yes	yes	yes	yes	yes	yes
Wald	131.3**	128.1**	132.4**	130.2**	128.5**	136.1**
Pseudo-R^2	0.0710	0.0813	0.0713	0.0818	0.0813	0.0716
Partial R^2 and F	0.6021 711.3	0.5766 694.8	0.5179 587.5	0.5411 678.4	0.6011 705.6	0.4947 514.7

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial productivity)

The estimation results reveal that convergence is accompanied by significant cluster effects in specific specifications of the productivity growth model (Table 3). The co-existence of agglomeration effects and a general dynamics towards convergence 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 3.3 per cent per annum. As distinguished from Delgado, Porter and Stern (2014), concomitance of convergence and agglomeration here occurs within the same spatial units. The highly significant Wald statistic shows that the explainatory variables jointly explain regionally varying productivity growth rates.

The positive impact of cluster strength on regional productivity is robust and statistically significant at the 5% level in all benchmark model specifications. This indicates that regions with specialised 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 effect show any significant effects at standard critical levels. This also holds when cluster diversity is decomposed in its constituent parts variety and balance.

Our findings are in part in accordance with evidence form other research studies. They match well with the discovery of Frenken, van Ooort and Verburg (2007) that related but not unrelated variety is advantageous for regional productivity growth. We find strong support for the presence of MAR and - with a special view on competition - Porter spillovers for regional competitiveness. However, while urbanisation economies do not seem to play a supporting role in productivity dynamics[17], the lack of evidence for diversification impacts does not necessarily exclude the presence of Jacobs spillovers. To throw light on this contentious point, we examine the specific number of regional clusters that stand behind the significant cluster strenght effect.

Slaper, Harmon and Rubin (2018) assess local and traded cluster impacts with respect to specialisation and balance on several regional performance measures for US metropolitan statistical areas (MSA). With regard to productivity growth our findings on the effects of R&D-intensive clusters are well in line with their results for traded clusters. For this type of cluster, the authors identify a positive and significant cluster strength effect and and a non-significant evenness effect. However, Slaper, Harmon and Rubin (2018) consider only 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, Shapiro and Vining (2008) 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, though.

A number of observed regional chracteristics are considered as control variables. Although the direction of their impacts can be interpreted in a meaningful way, only some controls exert a robust significance influence across different specifications.[18] A rise in the share of skilled workers is associated with a highly significant increase of productivity growth without exception. With respect to the sectoral breakdown, the expected effects are measured. Presumingly because productivity gains are limited in public, household or social security services, productivity growth is negatively affected by a high regional presence of the service sector. By contrast, industrial sectors offer more opportunities for productivity increases. Both effects prove to be highly significant.

Impacts from cluster specialisation may additionally emerge from neighbouring regions. 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 and 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 4 give no indication on the existence of such supplementary spillover effects.

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[17] Indicators for urbanisation economies like urban size and density (cf. Frenken, van Ooort and Verburg, 2007) do not significantly effect productivity growth in the panel data models.

[18] Detailed regression results can be obtained from the authors upon request.

Thus, virtually all potential spatial spillovers of productivity growth are already captured in delimiting the geographical range of R&D-intensive clusters.

Table 4: 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	-0.1744** (0.0637)	-0.1744** (0.0637)	-0.1743** (0.0638)	-0.1744** (0.0637)	-0.1744** (0.0637)	-0.1742** (0.0640)
Cluster strength	0.0012* (0.0006)		0.0013* (0.0006)			0.0013* (0.0006)
SL(Cluster strength)	0.0004 (0.0009)		0.0001 (0.0009)			-0.0003 (0.0010)
Cluster diversity		0.0014 (0.0047)	0.0032 (0.0046)			
SL(Cluster diversity)		0.0033 (0.0065)	0.0029 (0.0065)			
Cluster variety				0.0011 (0.0016)		0.0021 (0.0025)
SL(Cluster variety)				0.0015 (0.0023)		0.0057 (0.0058)
Cluster balance					0.0005 (0.0056)	-0.0031 (0.0084)
SL(Cluster balance)					0.0044 (0.0084)	-0.0141 (0.0201)
Controls	yes	yes	yes	yes	yes	yes
Wald	132.0**	131.6**	135.5**	132.7**	134.2**	139.5**
Pseudo-R^2	0.0714	0.0815	0.0717	0.0819	0.0814	0.0724
Partial R^2 and F	0.5838 612.0	0.5508 599.7	0.4974 464.5	0.5246 588.8	0.5771 608.27	0.4698 378.34
SLMlag	0.2203	0.1600	0.2225	0.1771	0.1621	0.2331
SLMerr	0.6114	0.6465	0.6362	0.6940	0.6479	0.6773

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial productivity), SLMlag: Panel Lagrange Multiplier test for spatial lag dependence, SLMerr: Panel Lagrange Multiplier test for spatial error dependence.

Up to now it can be concluded that specialised clustered areas (cluster specialisation) may be able to reap competitive advantages in the form of stronger productivíty growth. Yet, nothing is known on the relevance of the degree of specialisation. Because of non-significant regression coefficients of all measures related to cluster diversity, we do not expect productivity gains from a large number of clusters. But a strength-based effect can still arise from regional specialisation in only one or a few clusters. For that reason we additionally regress productivity growth on cluster dummy variables that indicate the number of R&D-intensive clusters in the regions. Panel A of Table 5 shows that significant growth effects result in regions with a strong presence of up to three clusters. No significant productivity effects arise from a broad specialisation on more than three clusters.

Finally, the issue of whether productivity growth effects from regional specialization can be associated with certain types of R&D-intensive clusters remains to be identified. 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. Here especially advantages from cluster specialisation in automobile production and machinery are disclosed (Panel B of Table 5). With some qualifications this also holds for the production of chemical and pharmaceutical products. Both estimation results are supportive for Marshallian externalites in productivity dynamics. Jacobs-type spillovers tend to be at least partially realised.

Table 5: Degree of specialisation and specific cluster specialisation

A. Degree of specialisation		B. Specific cluster specialisation	
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
Wald	166.7**	Wald	139.4**
Pseudo-R^2	0.0751	Pseudo-R^2	0.0537
Partial R^2 and F	0.5354 / 428.5	Partial R^2 and F	0.5289 / 489.6

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial productivity)

7. Empirical results II: Clusters and innovation growth

In addition to productivity growth, cluster theory backs up innovation growth as an essential factor of regional competitiveness (Camagni 2002; Martin, Kitson and Tyler 2006; Porter 1990, 1998, 2000, 2009). As for the analysis of productivity growth, we start examining the impacts from cluster strength and diversity within the baseline models. We then extend the model to examine the importance of spatial cluster spilovers for innovation growth. Finally, we focus on our interest on the extent of cluster specialisation and the significance of specific cluster effects in innovation dynamics.

Table 6: Convergence and cluster impacts on innovation growth (Baseline models)

	BM I	BM II	BM III	BM IV	BM V	BM VI
Initial pat. stock	-0.0135$^{(*)}$ (0.0070)	-0.0161* (0.0075)	-0.0148* (0.0074)	-0.0155* (0.0077)	-0.0161* (0.0074)	-0.0146$^{(*)}$ (0.0076)
Cluster strength	-0.0036 (0.0029)		-0.0034 (0.0028)			-0.0034 (0.0029)
Cluster diversity		0.0159 (0.0217)	0.0039 (0.0057)			
Cluster variety			0.0122 (0.0212)	0.0032 (0.0083)		-0.0023 (0.0130)
Cluster balance					0.0186 (0.0239)	0.0215 (0.0373)
Controls	yes	yes	yes	yes	yes	yes
Wald	18.7*	17.0*	18.8*	16.5*	17.0*	19.4*
Pseudo-R^2	0.0248	0.0227	0.0251	0.0223	0.0228	0.0253
Partial R^2 and F	0.8161 6566.8	0.8000 6550.1	0.7907 5620.8	0.8015 6551.5	0.8086 6553.6	0.8013 4917.03

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial patent stock)

Conditional convergence in innovation dynamics is effective but considerably lower than for the case of labor productivity (Table 6). The rate of convergence of regions to their own steady state amounts to 0.3 per cent per year. The conditionality of convergence results from the fact that dynamics also here depend on regional characteristics. As with productivity growth, the share of human capital as well as the regional sectoral composition affect the growth rate of innovation significantly. Additionally, innovation dynamics is positively related to the share of young workers.

As Table 6 shows, no direct cluster impacts at the level of small-scale NUTS 3 regions can be ascertained. Neither cluster strength nor cluster diversity in the own region exerts a significant influence on innovation growth proxied through the growth rate of the region's patent stock. The finding is preserved when cluster diversity is decomposed in its constituents, variety and balance. The non-significance at the small regional scale may be pandered by the modality how patent applications are filed. This issue has to be discussed in the context of spatial spillover effects.

In Table 7, estimation results for spatial models of inovation growth are reported. The outcomes confirm the low rate of convergence in presence of spatial cluster effects with the same set of relevant control variables. Direct cluster effects are still not supported. However, since spatial strength effects turn out to be postively significant, beneficial impacts of cluster specialisation on patenting growth seem to be present in larger contiguous areas. This may, at least, partially be explained by the fact that patent applications are counted at the inventor's place of residence, which does not necessarily coincide with firm location. Thus, when the innovation potential is partly used in the spatial environment of the inventor's place of residence, advantages of cluster strength will not fully become apparent in the own region. In this instance, effects from cluster specialisation are related to a larger regional scale.

Table 7: Convergence, cluster impacts and spatial effects on innovation growth (Spatial models)

	SM I	SM II	SM III	SM IV	SM V	SM VI
Initial patent per worker	-0.0162* (0.0069)	-0.0153* (0.0076)	-0.0157* (0.0074)	-0.0157* (0.0077)	-0.0161* (0.0075)	-0.0160* (0.0075)
Cluster strength	-0.0033 (0.0028)		-0.0032 (0.0029)			-0.0033 (0.0050)
SL(Cluster strength)	0.0096* (0.0048)		0.0113* (0.0051)			0.0111* (0.0050)
Cluster diversity		0.0221 (0.0227)	0.0165 (0.0224)			
SL(Cluster diversity)		-0.0215 (0.0304)	-0.0411 (0.0314)			
Cluster variety				0.0024 (0.0094)		-0.0022 (0.0142)
SL(Cluster variety)				-0.0022 (0.0012)		-0.0131 (0.0234)
Cluster balance					0.0184 (0.0251)	0.0205 (0.0377)
SL(Cluster balance)					0.0006 (0.0381)	0.0206 (0.0795)
Controls	yes	yes	yes	yes	yes	yes
Wald	23.6**	18.2*	27.0**	16.5(*)	17.2*	26.1*
Pseudo-R^2	0.0285	0.0231	0.0301	0.0223	0.0228	0.0294
Partial R^2 and F	0.8153 5627.5	0.7999 5610.9	0.7996 4365.9	0.8013 5612.2	0.8086 5613.9	0.7932 3565.7
SLMlag	0.0008	0.0097	0.0024	0.0024	0.0162	0.0002
SLMerr	0.0161	0.0017	0.0276	0.0000	0.0078	0.0121

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial patent stock), SLMlag: Panel Lagrange Multiplier test for spatial lag dependence, SLMerr: Panel Lagrange Multiplier test for spatial error dependence.

This perspective may be conducive to aligning the estimation results for small German regions with the findings on direct cluster impacts for large Canadian city-regions (Spencer et al. 2010). While Spencer et al. (2010) exposed a negative connection between clustering and patent rates on the individual industry basis, they find a weak positive relationship for overall rates at the regional level. Different patent generating functions and types of clusters are quoted for an explanation of the discrepancy. The dynamics of innovation activity has been placed to the foreground by Delgado, Porter and Stern (2014). Compared with German NUTS 3 regions, the authors estimated a much higher annual rate of convergence for industries in US economic areas (EA). At the same time, the authors ascertained a highly significant positive impact of own and related cluster strength on EA-industry patenting growth. In neither of these studies diversity effects are examined.

Table 8: Degree of specialisation and specific cluster impacts

A. Degree of specialisation		B. Specific cluster impacts	
Initial productivity	-0.0162* (0.0072)	Initial productivity	-0.1141* (0.0070)
1 SL(Cluster)	0.0377 (0.0565)	SL(LQAutoCl)	0.0104(*) (0.0056)
2 SL(Cluster)	0.1023(*) (0.0555)	SL(LQPharmaCl)	0.0082(*) (0.0048)
3 SL(Cluster)	0.0422 (0.0521)	SL(LQITCl)	-0.0259* (0.0111)
4 SL(Cluster)	-0.0491 (0.0590)		
> 4 SL(Cluster)	0.1026 (0.1060)		
Controls	yes	Controls	yes
Wald	23.0*	Wald	27.4**
Pseudo-R^2	0.0299	Pseudo-R^2	0.0290
Partial R^2 and F	0.7803 / 3956.1	Partial R^2 and F	0.7814 / 4913.0

Note: Heteroscedasticity-consistent (HC) standad 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 1st stage regression (instrumenting initial patent stock)

Using dummy variables for the number of clusters, no direct cluster impacts on patenting growth are revealed (Panel A of Table 8). However, in accordance with the findings on cluster strength, some evidence of a relatively high degree of cluster specialisation is established within a larger surrounding area. Regional specialisation on more than two clusters does not seem to generate additional benefits. Consistently, specific cluster impacts on innovation growth are only ascertained at a larger regional scale. They arise in particular from the production of motor vehicles and pharmaceutical products (Panel B of Table 8).

Somewhat more involved is the interpretation of the significant negative effect of IT clusters. This indicates a dampening effect of IT clusters on the overall growth of patent applications. One possible explanation may lie in high level of knowledge already achieved in IT cluster areas. As the knowledge stock in these areas is about six times greater than in all other districts, innovation growth apparently tends to fall short. Indeed, excessive co-location and increased competition of IT firms may bring diseconomies of agglomeration. Similarly, in studying the performance of US biotech firms, Folta, Cooper and Baik (2006) have found that marginal benefits of clustering become negative as clusters get large. The findings support the occurence of Marshallian externalites and in a limited extent additionally Jacobs externalities.

8. Conclusions

Strong regional clusters with highly competitive local firms are increasingly seen as a response to economic globalization by policy makers and regional development agencies. The notion that countries and regions with firms organized in clusters have a competitive advantage is closely related to the influential work of Porter (Porter 1990, 1998, 2000, 2003; Camagni 2002; Martin, Kitson and Tyler 2006). Because of the presumed connection between clustering and high productivity growth and innovation potential, 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, Porter and Stern 2014; Slaper, Harmon and Rubin 2018). In their investigation of cluster effects on firm growth, Maine, Shapiro, Vining (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 positive productivity and innovation growth in regions hosting one or 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 modelling framework.

For Germany, we find significant positive cluster effects on regional competitiveness in presence of conditional convergence. It is not cluster diversity that matters for productivity and innovation growth but cluster strength. While the impact of cluster specialisation on productivity growth is already measured at level of NUTS-3 regions, beneficial cluster effects for innovation growth are identified within larger regions via positive spatial spillovers. The effects of cluster strength on these performance measures are robust with respect to different model specifications. For productivity growth the cluster effects are conditional on regional covariates such as the proportion of skilled workers and employment shares in manufacturing and services. Innovation growth is additionally significantly influenced by the share of young workers.

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 exernalities 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 three R&D-intensive clusters in different technological fields. A somewhat higher degree of specialisation seems to be advantageous for innovation dynamics. Specific cluster effects on productivity growth emanate from the production of automotives, chemical and pharmaceutical prodcucts and machine construction. With regard to patenting growth, specific positive effects of automotive and pharmaceutical clusters are found. However, in IT clusters, congestion effects tend to outbalance cluster advantageous, indicating thet the optimal degree of agglomeration seems to have already surpassed.

With regard to policy recommendations, our results clearly show that cluster-based regional development approaches needs to be implemented carefully as not all types of clustering activities translate into higher productivity and innovation growth. Although our results generally show that cluster strength is associated with higher productivity growth, reality has proven that it is very difficult to copy successful examples of strong clusters (such as the Silicon Valley) in alternative regional context conditions (Hospers et al., 2008). In addition to the general role played by cluster strength, our results also point to the fact that positive productivity (and innovation) 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.

However, 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 deliberately cross sectoral and technological boundaries. An example for suhc a policy is the current setup of Germany’s leading edge cluster competition (Rothgang et al., 2015). Finally, our results also hint at the role of spatial spillovers from clustering, particularly with regard to their role for knowledge creation. 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 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 and knowledge creation in order to better identify the causal mechanisms at play in this relationship. With the limited time dimension at hand, our research had to start from the underlying assumption that a given 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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Appendix

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 - 27.3	Manufacture of basic iron and steel and of ferro-alloys; 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.
32	Manufacture of radio, televison 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)