Small Bus Econ
https://doi.org/10.1007/s11187-025-00999-3

RESEARCH ARTICLE

Hidden champions and knowledge spillovers: innovation-enhancing agglomeration effects and niche technology specificity

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Accepted: 2 January 2025

Abstract To achieve market and technology leadership, innovation is essential for niche market leaders. While research suggests that regions benefit economically from a high concentration of niche market leaders, it is still unclear which role locating close to one another plays for their innovation performance. Therefore, we contribute to existing literature that studies external factors of firm-level innovation. We analyze 1372 German niche market leaders and study whether (1) being located in a cluster improves their innovation performance and (2) if the impact of locating in a cluster varies depending on the diversity of industries within the cluster. We measured the spatial agglomeration using the location quotient. Our findings show that being located in a cluster increases the patenting rate by 1.49 times. This effect is more pronounced in clusters with more diverse industries, indicating a lower level of technology specificity. This suggests that technology specificity has an impact on a company's ability to take advantage of positive knowledge from other companies in the same cluster. Finally, we conducted several tests to ensure the robustness of our analysis. The Modifiable Areal Unit Problem (MAUP) refers to the discretionary choice of the spatial unit, and we tested different spatial unit levels to account for this. Additionally, we used entropy balancing to confirm the positive effect of cluster location on innovation, comparing with a control set of mass-market firms. Our study concludes with implications for both corporate management and public policy.

Plain English Summary Locating within industry clusters boosts innovation for German niche market leaders, increasing patent rates by a factor of 1.49. Our study shows that German niche market leaders innovate more when they are located in business clusters. Analyzing 1372 companies, we found that clusters with a greater mix of less similar industries further boost innovation by enhancing knowledge sharing. This means that being in a heterogeneous environment helps companies benefit from shared knowledge, making them more innovative. In practice, firm managers should enhance their companies' ability to absorb and use knowledge from other

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firms in the cluster. Active interaction and cooperation with similar firms are crucial. For policy-makers, supporting niche market leaders through improved infrastructure and vocational education can foster regional development and economic growth. Encouraging cooperation and knowledge exchange within clusters is essential for sustaining innovation and competitiveness.

Keywords Niche market leaders · Hidden champions · Spatial agglomeration · Knowledge spillovers · Innovation · Clusters · Technology specificity

JEL Classification M1 · O3 · R1

1 Introduction

Knowledge spillovers are a significant driver of innovation in high-tech firms (Audretsch et al., 2021a, 2021b; Baptista & Swann, 1998; Grashof, 2021). Yet, research has focused on the innovation-enhancing effects of knowledge externalities mainly in two contexts: (1) newly established ventures (start-ups) and (2) spin-offs from existing organizations. Start-ups typically filter and commercialize ideas not pursued by the original knowledge creators. In contrast, spin-offs, whether corporate or academic, leverage strong ties to parent organizations or universities (Civera et al., 2019; Wennberg et al., 2011).

In our study, we shift the focus to an under-investigated firm type: niche market leaders or "hidden champions" (Audretsch et al., 2021a, 2021b). We define these firms as those ranking among the top 3 in their global market or leading their continent, with annual revenues not exceeding $5 billion. This definition identifies firms that also belong to the partly overlapping categories of Mittelstand, family firms, and hidden champions, which have often been used in the literature as synonyms (De Massis et al., 2018a; Pahnke and Welter, 2019; Schenkenhofer, 2022). In addition to their niche market focus, key differentiating characteristics of niche market leaders are their "pro-active opportunity strategy, high investments in research and development (R&D), and a high degree of innovativeness" (Audretsch et al., 2021a, 2021b, p. 1279).

Given their highly specialized technologies, the effectiveness of how niche market leaders process and utilize external knowledge is debatable. Cohen and Levinthal (1989) suggest that firm-specific investments in a knowledge base enhance a firm's capacity to absorb and exploit external knowledge. The better a firm can process new ideas and technologies, the better it can commercialize absorbed knowledge (Kirschning & Mrożewski, 2023). Given the knowledge intensity of their technologies, niche market leaders are expected to exhibit a high absorptive capacity for knowledge spillovers. Therefore, our first hypothesis examines whether niche market leaders benefit from agglomeration effects in knowledge clusters and resulting knowledge spillovers (Acs et al., 2009, 2013; Ghio et al., 2015).

Yet, the specific nature of knowledge in niche technologies differentiates the spillover processes for niche market leaders from start-ups and spin-offs. The specificity of knowledge is characterized by its uniqueness and how it can be exchanged, understood, and harnessed for new purposes. Niche markets are characterized by a high degree of specificity of technologies and the inherent knowledge required for production processes (Audretsch et al., 2021a, 2021b). The question remains whether and how this specific knowledge can be absorbed and commercialized through spillovers. Thus, our second hypothesis investigates how the specificity of technology affects the agglomeration benefits of innovation activities. Clusters vary in industry composition, from homogeneous to heterogeneous (Delgado et al., 2014). The meaning of specificity can, therefore, be studied through the lens of industry composition. Specifically, we analyze whether the positive effect of cluster location on innovation activity is higher for industry-wise, more heterogeneous clusters. Technology specificity is assumed to be lower in more heterogeneous clusters, which in turn is thought to increase the capability to absorb and commercialize third-party knowledge. Therefore, we build on the concept of "sector fluidity," defined by De Massis et al., (2018b, p. 9) as the "extent to which information, knowledge, and resources can flow freely across industry boundaries" and elaborate on the notion of sector-based entrepreneurship. In particular, we posit that a lower industry specificity increases the possibilities for firms to absorb and commercialize knowledge (Sammarra &

Biggiero, 2008). The opportunities to combine different resources (and positively impact innovation) are likely to be hindered by the lack of industry heterogeneity, and thereby of sector fluidity, within the clusters (Schumpeter, 1934).

Empirically, we identify niche clusters using the location quotient (Wennberg & Lindqvist, 2010) and analyze the effect of cluster location on innovation activities through negative binomial regressions. Our sample includes 1372 German niche market leaders. We validate our findings with a sample of 124 Italian niche market leaders and compare them to a mass-market control group using entropy balancing (Hainmueller, 2012). Our results contribute to multiple literature streams.

First, we add to the literature on external drivers of firm-level innovation and the role of spatial agglomeration in innovation performance (Baptista & Swann, 1998; Delgado et al., 2014). Moreover, we contribute to the analysis of innovation for niche market leaders. Niche market leaders are major pillars of their economy as they have demonstrated remarkable economic resilience. They display above-average growth rates, contribute great volumes to exports, and are important training institutions in the respective vocational education system (Audretsch et al., 2021a, 2021b; Lehmann et al., 2019). Therefore, their strong economic performance adds significantly to regional performance (Benz et al., 2021). While we know that innovation is key for them, so far, research mainly analyzed internal factors of their innovation strategy (Schenkenhofer, 2022). However, we need to learn more about where they source external innovation inputs (Love et al., 2014). Lastly, we respond to De Massis et al.'s (2018b) call for sector-based studies by investigating the role of sector fluidity for niche market leaders.

The paper is structured as follows: Sect. 2 reviews the literature on the cluster-innovation link and the importance of agglomeration effects. We then delve deeper into the defining characteristics of niche market leaders and why innovation is key for them. Section 3 draws from the theory of knowledge spillovers and places it into the context of niche market firms. Sections 4 and 5 present our empirical analysis using negative binomial regressions. Finally, Sect. 6 concludes.

2 Theoretical background and review of literature

This study first investigates the influence of agglomeration effects and possible knowledge spillovers on the innovation output of niche market leaders. Our second hypothesis aims at unraveling the meaning of cluster composition concerning industry heterogeneity. As niche industries are highly specific, the second hypothesis analyzes if the specificity of cluster composition hinders the absorption and commercialization of niche market leaders and thus directly builds on our first hypothesis. Coherently, we have structured the theoretical background, which we draw from literature (Sect. 2). Section 2.1 presents the effects of cluster formation on innovation outputs at the firm level. Section 2.2 elaborates on why innovation is a key strategy of niche market leaders.

2.1 Innovation, spatial agglomeration, and knowledge spillovers

The field of economic geography investigates the extent to which the economic activities of firms and individual actors are geographically organized. It examines the extent to which locations and spatial agglomerations guide and incentivize economic behavior. The first contribution to link the economic benefits from externalities through locating in clusters was pioneered by Marshall (1890). He describes how locating in close proximity to other firms helps to recruit employees and nourish expertise and ideas.

Michael E. Porter's (1998) cluster concept defines clusters as geographic concentrations of interconnected companies, suppliers, and institutions in related industries. Clusters influence corporate strategy and innovation performance. To this end, the knowledge spillover theory investigates how actors harness knowledge through agglomeration effects and transform it into marketable goods or new ventures. Here, it is crucial that some firms do not invest in the accumulation of knowledge, such as R&D, but absorb the knowledge as a positive externality from third parties (Acs & Audretsch, 1988; Acs et al., 1994a; Anselin et al., 1997).

The study of knowledge spillovers includes research on the role of economic clustering in promoting growth and the theory of endogenous economic growth (Grossman & Helpman, 1994; Romer, 1990), which explores the relationship between knowledge accumulation, innovation, and economic development (Aghion & Howitt, 1992; Romer, 1986, 1990). Knowledge spillovers are affected by geographic proximity, contributing to regional differences in innovation and economic growth (Fallah & Ibrahim, 2004; Döring & Schnellenbach, 2006).

The knowledge spillover theory of entrepreneurship aims at understanding how knowledge spillovers contribute to creating new ventures (Audretsch, 1995; Audretsch & Keilbach, 2007). Traditional views of knowledge accumulation and innovation in firms, such as Griliches' (1979) firm knowledge production function, may not fully apply to small enterprises. Instead, Audretsch's (1995) knowledge spillover theory suggests that firms emerge to take advantage of external knowledge, driving innovation and new venture creation (Audretsch & Lehmann, 2005).

To this effect, we align with a field within knowledge spillover research that studies how clustering and spillover effects drive product innovation and firm activity (Acs & Audretsch, 1988; Acs et al., 1994b; Audretsch & Feldman, 1996; Audretsch, 1998; Baptista & Swann, 1998; Feldman, 1994, 2000). Jaffe (1986) was one of the first to study the impact of locating within a cluster on firms' innovation output. Acs et al., (1994a, 1994b) examined why small firms can innovate with low R&D expenditures, while Audretsch and Feldman (1996) found that spatial concentrations enhance innovation activity. Other studies explored the innovativeness of firms in industry clusters (Baptista & Swann, 1998), the effects of industrial diversity and specialization on innovation (Paci & Usai, 1999), and knowledge flows between European regions (Maurseth & Verspagen, 2002). Recent research by Grashof (2021) found a positive correlation between cluster membership and innovativeness, and Audretsch et al., (2021a, 2021b) examine differences in innovation outputs between startups and incumbent firms stimulated by knowledge spillovers. We extend this literature and examine the cluster-innovation link at a firm level for niche market leaders.

2.2 Innovation as a key characteristic of niche market leaders

Niche market leaders are firms deploying a niche marketing approach. Niche marketing has been defined as the "process of carving out, protecting, and offering a valued product to a narrow part of a market that displays differentiated needs" (Toften & Hammervoll, 2013, p. 280). Thus, niche marketing involves a number of facets (Ottosson & Kindström, 2016; Parrish et al., 2006):

1. Niche marketing results in product differentiation, offering valuable and highly specialized products and services.
2. Niche world-market leaders often achieve technology leadership, which results in high entry barriers for competitors.
3. The narrow market implies a high dependency and specific investments in close-customer relationships.
4. Niche strategies tailor their offer to unique preferences and a narrow and well-defined group of potential buyers.
5. Niche marketing involves market segmentation, which implies that large heterogeneous markets are divided into smaller, homogeneous markets.

Niche marketing literature describes niche market leaders as mostly unknown to the public due to their low brand awareness of the company and its products (Schenkenhofer, 2022). Due to their mostly non-urban location and their absence from listings on stock exchanges, they usually deliberately fly under the radar to secure market shares (Schmid & Welter, 2024). They are mostly family-run, and the niche market setting drives continuous internationalization. The technology dependency of their customers implies that they are exposed to literally any demand that arises worldwide. As a result, they generate a majority of their sales from international businesses (Audretsch et al., 2018).

Niche market leaders, often technology leaders in their specialized markets, continuously innovate to meet quality and safety standards (De Massis et al., 2018a). Due to their limited buyer spectrum, innovation is a core strategy to secure market shares. This focus has made innovation the most studied aspect of niche market leadership (Schenkenhofer, 2022), with research examining customer roles, HR management practices (Audretsch et al., 2021a, 2021b), and geographic distribution's impact on regional innovation development (Benz et al., 2021). However, the influence of external innovation factors, like agglomeration effects, remains underexplored. We hypothesize that niche market leaders benefit from spillover effects due to spatial proximity, which we will further explore in the next section, emphasizing cluster heterogeneity's role.

3 A spillover theory for niche market leaders

In this section, we adapt the theory of knowledge spillovers and apply it to niche market leaders. First, we present the general rationale of knowledge spillovers. Then, we continue to elaborate on how niche market leaders benefit from agglomeration effects and the resulting knowledge spillovers. This is explained in Sect. 3.1. The section after that, 3.2, builds on that to further underpin the theoretical foundations for our second hypothesis, in which we question whether the agglomeration effects through locating in more industry-wise heterogeneous clusters increase the positive effect on innovation activity. The purpose of this second hypothesis is to understand if knowledge of niche technologies is too specific to be absorbed through spillovers. Thus, we extend our first hypothesis to gain a deeper understanding of the sector fluidity of knowledge resources as proposed by De Massis et al. (2018b).

3.1 Spatial agglomeration and niche market leaders

Knowledge can be exchanged between individuals or institutions either consciously or unconsciously. Conscious exchange, often referred to as knowledge transfer, is characterized by a deliberate purpose or goal. Conversely, unconscious exchange is termed spillover. A spillover occurs when knowledge that was initially exchanged consciously extends beyond the original sender-receiver relationship and reaches third parties. Research indicates that factors such as proximity, frequency of contact, and absorptive capacity are essential for the absorption and utilization of knowledge (Fallah & Ibrahim, 2004).

The literature distinguishes different types of knowledge spillovers: MAR (Marshall-Arrow-Romer), Jacobs, and Porter spillovers. The MAR spillovers emerge through concentrations of an industry or similar industries in a certain region. Similar input goods, production processes, and technology applications help firms from the same industries through specialization advantages (Arrow, 1962; Marshall, 1890; Romer, 1986). Firms benefit from economies of scale they generate through the shared input goods, such as better labor market pooling. The agglomeration effect, e.g., rests in specific human capital that is better available in close geographic proximity, as better employment opportunities attract more talent. Jacobs' (1969) contribution, on the other hand, assumes "that the variety of local activities plays a major role in the innovation process given that it enhances the economy's capacity of adding still more goods and services" (Paci & Usai, 1999, p. 381). Thus, spillovers emerge across industries. Therefore, they occur especially frequently in urban areas as the diversity of knowledge is highest there. For Jacobs, spillovers result from exchanging complementary knowledge and the cross-fertilization of ideas. Finally, Porter (1998) describes spillovers as occurring in specialized industries that foster economic growth. For him, local competition is key to innovative activity.

Our study views the arising niche spillovers as MAR in nature. Thus, we assume that niche market leaders can exploit spillover externalities through their high specialization within the same or similar industries. The high specialization of niche technologies results in highly homogenous industries that are heterogeneous among each other. Niche market leaders often settle in the hometowns of the company founders or settle near associated mass-market customers (such as the automotive cluster in Stuttgart). While niche market leaders thus differ from unicorns, start-ups, and spin-offs, as described further above (Chesbrough, 2003), they share factors with them that explain possible spillovers in niche clusters. Among them, they are thought to emulate a certain absorptive capacity (Nieto & Quevedo, 2005). Moreover, the rural endowment is likely to allow spillovers in extra-firm conversations (Pouder and St. John, 1996). Thus, we follow:

> *H1*: Locating in a cluster has a positive impact on the innovation output of niche market leaders.

3.2 Cluster heterogeneity and technology specificity

In our second hypothesis, we extend the idea that agglomeration effects benefit niche market leaders and investigate if the effect of cluster location on innovation decreases with technology specificity

(Sammarra & Biggiero, 2008). Our line of reasoning rests on the concept of "sector fluidity" as introduced by De Massis et al. (2018b). Thus, we extend efforts by De Massis et al. (2018b) that call for research to better disentangle the notion of the sector. In their analysis, they study the mechanisms through which the industrial sector influences phenomena related to innovative ventures and the methods through which actors "interact with sectors to prospect, develop, and exploit" opportunities (p. 2).

To this effect, sector-based capabilities are the capacities, such as processes or routines of firms, to "prospect, develop, and exploit opportunities by reconfiguring human, social, and financial resources within and across industry sectors" (p. 9). Thus, sector-based capabilities enhance the prevailing understanding of industry-specific determinants, processes, and outcomes of innovative activity. A sector-based analysis of innovation, therefore, warrants an analysis of resource heterogeneity in sectors. In line with Schumpeter (1934), De Massis et al. (2018b) argue that the recombination of heterogeneous resources and information levels can result in new market equilibria. Niche sectors are highly specific and thus emulate a low sector fluidity. A low sector fluidity is capable of elevating the value, inimitability, and rarity of resources, making sectoral capabilities more valuable to the individual innovating firm. Therefore, we argue that the cluster-innovation link is stronger in more heterogeneous industries. A high technology specificity associated with niche market firms may prohibit the exchange and applicability of knowledge. We argue that heterogeneity within the industry clusters could help to reconfigure resources and thus create new ideas and foster innovation (Schumpeter, 1934). Summarizing, we follow:

> *H2*: The effect of cluster location on the innovation output of niche market leaders is stronger for industry-wise, more heterogeneous clusters.

4 Research design

4.1 Sample, data, and methods

In this study, we analyze if niche market leaders benefit from agglomeration effects in the shape of knowledge spillovers. In a second step, we are keen to find out if these effects are stronger for industry-wise, more heterogeneous clusters. To investigate these questions empirically, we examine a German sample of 1372 niche market leaders since there are sufficiently many niche market leaders existent within Germany. Selecting a sufficiently large sample is indeed essential, as it includes many different industries and possible agglomerations. The sample thus allows us to analyze the impact of niche spillovers on their innovation success. Our bottom-up sample selection of niche market leaders is based on the criteria that they must rank among the top 3 firms in their market (based on worldwide market shares), and their revenues do not exceed 5 billion $ per year. The revenue limit helps to restrict niche markets that are narrow in nature (Audretsch et al., 2021a, 2021b). In line with Schenkenhofer (2022), the sampling is grounded on an in-depth analysis of German niche markets as well as it incorporates numerous regional niche world-market leader registers of German chambers of industry and commerce, such as the IHK Arnsberg, IHK Schleswig–Holstein, or the IHK Chemnitz.[1] The companies in the dataset have a mean age of 99 years, have 3193 employees on average, and are distributed across 18 industries, as Table 1 presents in more detail. 63.3% of the companies are located in non-urban areas, which are distributed decentrally throughout the country. 61.9% are still family-owned. On average, the firms bestow a mean revenue of 640€ Mil. between the years of 2014 and 2018. The firm data was retrieved through an in-depth analysis of firms' annual reports and firms' homepages. The three largest industries in our sample are mechanical engineering, architecture and construction, and automotive. To illustrate this, we would like to present some exemplary niche-market leaders from these industries. The company Gebr. Heller was founded by Hermann Heller in Nuertingen (Baden-Wuerttemberg) in 1894. They are a mechanical engineering firm and a market leader for CNC machine tools and manufacturing systems. Brose is a car parts firm based in Coburg in the automotive industry. It was founded in 1908 and is a market leader for various car parts such as door or window components.

[1] As no single data source exists to distinguish hidden champions, we use knowledge from local market reports provided by regional chambers of industry and commerce.

Table 1 Industry overview of the niche market leaders (in %)

Industry	%
Mechanical Engineering	32.29
Architecture & Construction	12.02
Automotive	7.80
Electrical Engineering	7.50
Consumer & Retail	7.29
Chemical Engineering	6.20
Medical Engineering	4.15
Food	3.35
Other	3.35
Metal Ware	3.13
Rubber & Synthetics	2.48
Software	1.53
Metal Production	1.46
Textile	1.31
(Renewable) Energy	1.09
Logistics	1.09
Wood	0.87
Paper	0.73
Shipbuilding	0.58
Communication	0.29
Finance & Insurance	0.29
Agriculture	0.15
Total	100

The sample is built on a set of niche global market leaders from Germany. Germany was chosen as a database, as sufficiently many niche market leaders reside in Germany. Selecting a sufficiently large sample is essential to cover possible agglomerations. The sample uses an in-depth analysis of German niche markets and incorporates market registers of regional chambers of industry and commerce. Thus, the sample was built bottom-up, i.e., including niche market leaders one by one into the sample. The market leadership was then controlled through company self-assessments of market leadership. Therefore, the company's online records and website were analyzed thoroughly. Firms were included in the sample if they ranked among the top 3 firms in their market based on market shares. Their revenues must not exceed 5 billion $, which serves to delineate mass from niche markets

Goldbeck is a construction company that was founded in Bielefeld in 1969. It is a market leader for above-ground car parks.

But are there niche clusters? In the literature, there are several approaches for identifying clusters (Brenner, 2006). These can basically be divided into quantitative and qualitative approaches. Quantitative methods include, e.g., the location coefficient (Wennberg & Lindqvist, 2010) or the cluster index (Sternberg & Litzenberger, 2004). The cluster index was developed to identify spatially concentrated industrial specialization. For this purpose, it measures relative industrial density as well as spatial concentration. This is complemented by relative firm size to compensate for differences in firm size. Qualitative methods rely on case studies or in-depth analysis of regional entities by analyzing markets and socio-cultural counterparts, such as the Cluster Star method. The Cluster Star method of the European Observatory for Clusters and Industrial Change performs a quantitative–qualitative analysis (Hollander, 2020). For this, clusters are classified into high-performance medium- and base-performance clusters. In addition to the location coefficient for measuring industry specialization, the classification is based on a qualitative assessment of the clusters using the categories of size, productivity, performance, and innovativeness. We follow most of the literature on identifying clusters and use a stage-based approach such as, e.g., Wennberg and Lindqvist (2010). Our focal measure for identifying clusters relies on the location quotient, in addition to adhering to numerous studies in the literature that followed a similar approach (e.g., Delgado et al., 2014).

4.1.1 Benchmark case

We apply a benchmark case that uses the regional clustering of niche market leaders per regional unit. Here, we simply analyze the number of niche market leaders in a zip code area per 100,000 inhabitants without clustering (*Niche Firm Intensity*). The reference for this method is Benz et al. (2021), who apply this procedure to the number of niche market leaders per regional authority district. Without clustering, we do not expect this variable to positively determine the innovation performance of niche market leaders.

4.1.2 Cluster-innovation link

In our next step, we identify clusters by calculating the location coefficient for the concentration of niche market leaders in the respective zip code areas. We refer to cluster strength "by measuring the degree of agglomeration of firms in interconnected industries" (Wennberg & Lindqvist, 2010, p. 227). First, we aggregate our data to a specific geographical entity, which is the postal code area in our case. In the second step, we aggregate related industries into clusters by analyzing the industries in which niche market leaders operate. Consequently, an indicator must be determined that reflects the economic activity of the cluster (cluster strength). In our case, the cluster strength is considered at the company level, i.e., the number of niche market leaders from a similar industry and geographical area. Finally, the last step results in a measure that can be used to map the cluster strength, which is the relative value of the location quotient. The location quotient is calculated as $(E_{ij}/E_i)/(E_j/E)$, where E describes the agglomeration measure, i.e., the number of firms in our case. E_{ij}/E_j is the share of firms of industry i of a certain region j divided by the overall number of firms in a certain industry i. E_j/E is the share of firms in a certain region divided by the overall number of firms in the sample.

4.1.3 Robustness check: MAUP analysis

To test for the robustness of the chosen external environmental entity, adjacent zip code areas are included in an additional analysis. Theoretically, spatial concentrations can now be detected even if niche market leaders are located in neighboring zip code areas. Of course, this approach could be extended even further, a problem that is known in the literature as MAUP. The Modifiable Areal Unit Problem (MAUP) "refers to the discretionary choice of the spatial unit used to analyze geographic-based phenomena" (Cainelli et al., 2020, p. 421). Relying on spatial boundaries that are pre-defined through, e.g., political, units can bias statistical results. However, clusters that are too large the other way around lose significance with respect to the specificity of spatial effects (Wennberg & Lindqvist, 2010). Thus, we restrict ourselves to expanding to neighboring zip code areas. This procedure allows us to understand how far spillover effects can reach.

4.2 Measures

In this section, we present the variables used in the empirical analysis, as summarized in Table 2. We first describe our dependent variable and then present the independent and control variables.

4.2.1 Dependent variable

As the effect of knowledge spillovers cannot be measured directly, patents have often been used in literature to measure innovation activity increased by spillovers. Other measurements are based, for example, on innovation developments in companies. This paper uses granted patents to measure the innovation activity of niche market leaders, drawing from a plethora of other studies (Grashof, 2021; Paci & Usai, 1999).

4.2.2 Independent variables

We follow a two-step approach for all explanatory variables, numbered 1 and 2. The first step uses clustering based on zip code areas used as spatial units, applying the condition to incorporate at least three firms to establish a cluster. Explanatory variables with the number 2 in the index refer to the second step (MAUP analysis), where neighboring zip code areas were also included to identify clusters. We use a measure of the niche market leader distribution (*Niche Firm Intensity*) analogous to Benz et al. (2021), who measure the spatial concentration of niche market leaders. We use it as a base level to measure if the niche market leaders' concentration per 100,000 inhabitants in a post-digit area has an effect on innovation activity without clustering. While Benz et al. (2021) use German districts, we use zip codes and their first two numbers. The variables $cluster_1$ and $cluster_2$ describe dummy variables that indicate whether a niche market leader belongs to a cluster or not. Finally, the location quotient (*LQ*) is also included in both steps and is calculated as described above.

4.2.3 Control variables

Our control variables are taken from literature that has already investigated determinants of innovation activity. In line with other studies on the cluster-innovation link on a firm level, we included measures for firm age, firm size, market segment, economic performance, the rural–urban divide, family ownership, and industry effects (Fisch et al., 2022; Grashof, 2021).

A total of 139 clusters were identified, which are presented in more detail in Table 3. Table 4 and 5 exemplarily present a few clusters more in detail. In the second step, however, neighboring postal code areas are also included. Theoretically, the three companies here can also be distributed across different postal code areas, which are, however, close to the borders of neighboring postal code areas. Since a company can thus come from three different zip code

Table 2 Variable definitions and data sources

Variable	Description	Source
Innovation performance (DV)	The total number of granted patents for the respective company measured the innovation activity of the companies	German Register for Trademarks and Patents
$Cluster_1$	A dummy variable that takes the value one if a niche market leader is located in a cluster	Own calculation
$Cluster_2$	Same as cluster 1, but for a wider range of clusters, including also adjacent postal code areas	Own calculation
$INDS_1$	Regional industry strength is calculated from the concentration of niche market leaders in the individual cluster of industry in relation to the total number of niche world-market leaders emerging in the industry	Own calculation
$INDS_2$	Same as $INDS_2$, but for a wider range of clusters, including also adjacent postal code areas	Own calculation
CS_1E_i	The cluster strength is calculated from the ratio of niche market leaders in the cluster relative to the number of niche market leaders in the respective location. In the divisor, all companies in the cluster are taken into account, irrespective of the industry to which they belong	Own calculation
CS_2E_i	Same as CS_1, but for a wider range of clusters, including also adjacent postal code areas	Own calculation
LQ_1	Dummy variable indicating a cluster for $LQ \geq 1.25$, the cut-off value as in Miller et al. (2001)	Own calculation
LQ_2	Same as LQ_1, but for a wider range of clusters, including also adjacent postal code areas	Own calculation
Niche Firm Intensity	Number of niche market leaders per post-digit area per 100,000 inhabitants	Own calculation
Firm age	Describes the age of the companies measured in years	Firms' annual reports, firms' homepages
Family ownership	Dummy variable that takes on the value 1 if the company is owned majorly through one family	Firms' annual reports, firms' homepages
Revenues	Describes the revenues of the companies in € million and is the average between 2014 and 2018	Firms' annual reports, firms' homepages
Firm size	Describes the size of companies measured by the number of employees and the average between 2014 and 2018	Firms' annual reports, firms' homepages
Non-urban	Dummy variable that takes on the value 1, if the company has its headquarters in a place with less than 50,000 inhabitants	Firms' annual reports, firms' homepages
Industry-to-industry	Dummy variable that takes on the value 1 if the company is predominantly an industry-to-industry company	Firms' annual reports, firms' homepages
Cluster size	Describes the number of niche-world market leaders located in a cluster	Own calculation
Mechanical Engineering	Industry dummy variable	Firms' annual reports, firms' homepages
Architecture & Construction	Industry dummy variable	Firms' annual reports, firms' homepages
Automotive	Industry dummy variable	Firms' annual reports, firms' homepages
HHI	Herfindahl–Hirschman Index. The index measures the market concentration for an industry through the sum of the squared market shares of a firm within an industry	

Table 3 Cluster and industries

	Industry	Number of clusters
Industry 1	Mechanical Engineering	52
Industry 2	Architecture & Construction	22
Industry 3	Automotive	16
Industry 4	Electrical Engineering	12
Industry 5	Chemical Engineering	11
Industry 6	Consumer & Retail	11
Industry 7	Medical Engineering	5
Industry 8	Food	4
Industry 9	Metal Ware	3
Industry 10	Rubber & Synthetics	2
Industry 11	Textile	1
Total		139

We identify clusters using a structured procedure as applied by Wennberg and Lindqvist (2010). This structured approach uses several steps. First, data needs to be aggregated to a certain specific geographical entity. Using a German sample of firms, geographic data is best analyzed using postal code areas. Then, the agglomeration measure needs to be selected, which is the number of world-market leaders in our case. This reflects the economic activity in a geographically bound space (cluster strength). Finally, a measure needs to be calculated that expresses the cluster strength, which is the location quotient (LQ). Overall, 139 clusters could be identified

areas if they all border on each other, a further condition is formulated that the zip code areas must share at least two borders.

4.3 Descriptive statistics and correlation matrix

Table 6 presents the descriptive statistics on our variables. The dependent variable *innovation* suggests that, on average, niche market leaders from our sample withhold 505 patents, while some firms reach scores over 20,000. The firm age ranges between 13 and 920 years; 61.9% of the firms are still family-owned, and 63.3% of the firms reside in non-urban areas. The correlation matrix (Table 7) reveals that the highest correlations exist between *firm size* and *revenues* (0.671). No correlation of the independent variables is over 0.7; thus, multicorrelation is absent.

5 Results and discussion

5.1 Main analysis

Our analysis investigates the influence of cluster location on the innovation activity of German niche market leaders. For our first hypothesis, we examine the clustering of niche market leaders in the respective postal code area. In the second step, we examine how narrower and more specific clusters are able to foster innovation. Table 8 presents our results. While we kept the control variables stable throughout all of the models, model 1 depicts the scenario of our main independent variable $cluster_1$. The results from model 1 suggest that locating

Table 4 Exemplary cluster analysis (for one of the Medical Engineering clusters)

	Firm	Residence	Niche product	Industry
Medical Engineering	Aesculap GmbH Co. KG	Tuttlingen	Chirurgical instruments	Medical Engineering
Medical Engineering	KLS Martin Group (Gebr. Martin)	Tuttlingen	Chirurgical instruments	Medical Engineering
Medical Engineering	Karl Storz SE	Tuttlingen	Chirurgical instruments	Medical Engineering

Table 5 Exemplary cluster analysis (for one of the Chemical Engineering clusters)

	Firm		Niche product	Industry
Chemical Engineering	Almatis	Ludwigshafen	Special aluminum oxide	Chemical Engineering
Chemical Engineering	Dr. Woellner Holding	Ludwigshafen	Soluble silicates, process chemicals	Chemical Engineering
Chemical Engineering	Renolit	Worms	Chemical industry plastics	Chemical Engineering

Table 6 Descriptive statistics

	Obs	Mean	Std Dev	Min	Max
Innovation	1000	503.218	1738.483	0	23,401
Cluster	1372	.558	.497	0	1
Firm age	1050	98.602	70.814	13	920
Family ownership	1096	.619	.486	0	1
Revenues	925	640.237	1257.379	4.8	19,538.53
Firm size	930	3193	6719.353	40	75,354
Non-urban	1372	.633	.482	0	1
Industry-to-industry	1372	.865	.342	0	1
Cluster size	1372	4.4	5.727	0	25

The dependent variable innovation reveals niche market leaders to own 503 patents in their mean value. The firm age averages 99 years. While almost 62% of the firms are still family-owned, the majority of the firms reside in non-urban areas (63%). On average, the firms in our sample bestow revenues of over €640 million. Most firms are serving industry-to-industry markets. The industry analysis shows that 32% are mechanical engineering firms, 12% are architecture and construction firms, and 8% are located in the automotive industry

in niche clusters exhibits a strong positive effect on the innovation activity of niche market leaders (beta = 0.397**), therefore supporting hypothesis 1. As our dependent variable is the number of granted patents, we use a negative binomial estimator to account for overdispersed count data (Vismara, 2018; Wang et al., 2019). Models 2 and 3 present the results for our second hypothesis. Here, the clusters were refined and investigated clustering only for industries that subsume industries similar on a SIC2 or SIC3 specificity level. Corresponding to our theoretical assumptions, more homogenous and thus more specific clusters are less able to increase innovation performance, supporting hypothesis 2. The results from model 1 (Cluster Alpha, SIC1) are replicated in model 2 (Cluster Beta, SIC2), but both with a reduced coefficient and statistical significance. Model 3 reinforces these results as the effect disappears entirely (Cluster Gamma, SIC3). Thus, it seems as if a certain heterogeneity inherent in cluster composition indeed helps to combine a greater variety of knowledge entities (De Massis et al., 2018b; Schumpeter, 1934).

Models 4 and 5 describe robustness checks using similar independent variables, which will be discussed in the section further below. Model 6 shows

Table 7 Pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Innovation	1.000								
(2) Cluster	0.057*	1.000							
(3) Firm age	0.020	0.037	1.000						
(4) Family ownership	0.020	0.116***	0.075**	1.000					
(5) Revenues	0.364***	−0.004	0.043	0.019	1.000				
(6) Firm size	0.373***	0.020	0.088**	0.024	0.671***	1.000			
(7) Non-urban	−0.090***	0.097***	−0.052*	0.141***	−0.131***	−0.130***	1.000		
(8) Industry-to-industry	0.060*	0.165**	−0.052*	−0.026	0.008	0.010	0.058**	1.000	
(9) Cluster size	0.027	0.494***	0.006	0.077**	−0.025	−0.018	0.081***	0.125***	1.000

*Significance at the 10% level, **significance at the 5% level, ***significance at the 1% level

Table 8 Negative binomial regressions

	(1) Innovation	(2) Innovation	(3) Innovation	(4) Innovation	(5) Innovation	(6) Innovation	(7) Innovation
Cluster$_1$ Alpha	0.397**						
	(0.157)						
Cluster$_1$ Beta		0.370**					
		(0.210)					
Cluster$_1$ Gamma			−0.402				
			(0.323)				
INDS$_1$				2.019***			
				(0.510)			
CS$_1$E$_i$					6.623**		
					(3.057)		
LQ$_1$						0.299**	
						(0.137)	
Niche Firm Intensity							−0.001*
							(0.001)
Firm age	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Family ownership	−0.440***	−0.395***	−0.419***	−0.373***	−0.429***	−0.413***	−0.394***
	(0.129)	(0.130)	(0.129)	(0.128)	(0.129)	(0.129)	(0.130)
Revenues	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-urban	−0.165	−0.176	−0.144	−0.095	−0.176	−0.139	−0.107
	(0.127)	(0.128)	(0.127)	(0.126)	(0.128)	(0.127)	(0.129)
Cluster size	−0.023	−0.012	−0.005	−0.028*	−0.022	−0.020	−0.002
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
Industry-to-industry	0.411**	0.501***	0.536***	0.464**	0.489**	0.450**	0.565***
	(0.199)	(0.194)	(0.196)	(0.194)	(0.196)	(0.198)	(0.197)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.564***	−1.575***	−1.556***	−1.682***	−1.645***	−1.588***	−1.587***
	(0.236)	(0.238)	(0.239)	(0.235)	(0.239)	(0.236)	(0.238)
Sample size	698	698	698	698	698	698	698
McFadden's *R*-squared	0.07	0.06	0.06	0.08	0.06	0.06	0.06

Standard errors are in parenthesis; please note: firm size is included as an exposure variable; Cluster$_1$ is a dummy variable that takes the value 1 if a niche market leader is located in a cluster; Cluster Beta and Cluster Gamma describe cluster formations based on SIC2 and SIC3 levels

***$p<0.01$, **$p<0.05$, *$p<0.1$

the effect through clustering by applying the location quotient LQ_1, which is the base for our cluster dummy variable in model 1. LQ_1 shows a positive effect, as expected. Model 7 describes the benchmark scenario by analyzing the case without clustering, which is mapped analogously to Benz et al. (2021) with the variable *Niche Firm Intensity*. Without clustering, the mere concentration of niche market leaders is unable to reveal a performance-enhancing effect on innovation activity (model 7).

Table 9 (models 8 to 11) tests for the MAUP. Applying a different cluster identification here also includes neighboring postal code areas and thus describes a wider range of clusters. The cluster effects disappear when neighboring postal code areas are included. This result suggests that the cluster effects

Table 9 Negative binomial regressions (MAUP analysis)

	(8) Innovation	(9) Innovation	(10) Innovation	(11) Innovation
Cluster_2	0.277			
	(0.201)			
IND_2		1.662		
		(1.174)		
$\text{CS}_2\text{E}_\text{i}$			0.595	
			(0.616)	
LQ_2				0.088
				(0.141)
Firm age	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Family ownership	−0.424***	−0.416***	−0.412***	−0.419***
	(0.129)	(0.129)	(0.130)	(0.130)
Revenues	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Non-urban	−0.174	−0.119	−0.153	−0.135
	(0.128)	(0.128)	(0.127)	(0.128)
Industry-to-industry	0.531***	0.539***	0.512***	0.533***
	(0.195)	(0.195)	(0.196)	(0.196)
Cluster size	−0.012	−0.013	−0.011	−0.009
	(0.015)	(0.015)	(0.015)	(0.015)
Industry dummies	Yes	Yes	Yes	Yes
Constant	−1.720***	−1.662***	−1.600***	−1.604***
	(0.265)	(0.250)	(0.244)	(0.253)
Sample size	698	698	698	698
McFadden's *R*-squared	0.06	0.06	0.06	0.06

Standard errors are in parenthesis; please note: firm size included as exposure variable; cluster_2 is the same as cluster_1, but for a wider range of clusters including also adjacent postal code areas

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

appear within one postal code area and underline the role played by close geographic proximity. Regarding the overall size of knowledge spillovers, we are also in line with previous findings. While the spillovers in our German sample, on average, are limited to 37 miles, Anselin et al. (1997) also find spillovers of just under 50 miles for a US sample. Another study tests for distance-varying types of spillovers. They differ between inter- and intraregional spillovers using the cut-off value of 50 miles, based on the average daily US commuting distance.

Moreover, the control variables also reveal a number of interesting effects. Family ownership has a negative effect on the innovation activity of niche market leaders. A broad literature has found mixed effects on the relationship between family influence and innovation (e.g., Sharma et al., 1997). We classify ourselves with studies that show that family ownership has a negative effect on the innovation activity of firms (Lorenzo et al., 2022). Furthermore, industry-to-industry positioning seems to strongly drive innovation in niche markets.

Our results thus show that cluster effects exist in niche markets, and firms that are part of such clusters can generate positive benefits for innovation activity. We hypothesize that positive externalities in the form of MAR spillovers are responsible for this. Applying a wider geographical spread reveals that cluster effects are limited to the smaller geographical unit of one postal code area. This insight provides information about the actual size of clusters and the extent of spillover effects.

5.2 Non-linearity, robustness tests, and industry concentration

The actual relation between cluster location and innovation activity could be non-linear (Bell, 2005; Wennberg & Lindqvist, 2010). Congestion in the cluster could indeed lead to hyper-competition, which in turn could create a threshold for positive agglomeration effects. Theoretically, congestion could cause resource shortage in a cluster that cushions the positive effects of locating in a cluster. For example, firms could fall short of the human capital supply when competing for talented employees. Addressing this discussion, we re-estimate our models, including the squares of our continuous explanatory variables. The results (Table 10) show that including the squared terms of our metric-independent variables does not suggest the presence of a non-linear effect.

To check the robustness of cluster influence, we calculate a number of other cluster measures (Table 8 and 9). Both $INDS_1$ and $INDS_2$, as well as CS_1E_i and CS_2E_i, are relative values. $INDS_1$ and $INDS_2$ describe the regional industry strength, which is determined from the concentration of niche market leaders in individual clusters in an industry in relation to the total number of niche market leaders emerging in the industry. CS_1E_i and CS_2E_i describe the cluster strength, which is calculated from the ratio of the number of niche market leaders in the cluster to the number of niche market leaders at the respective location, whereby all companies are included in the divisor, irrespective of the industry to which they belong in the cluster. Overall, the results support the findings of our primary independent variable *cluster$_1$* and thus underline the meaning of geographical proximity for the innovation performance of niche market leaders. Adding to that, we calculate a Herfindahl–Hirschman Index (HHI) (Table 11) to control for industry concentration. While the results indicate that a higher concentration within an industry shows a strong negative effect, the positive effect of cluster location on innovation remains robust. The effect of the HHI indicates that a higher market concentration lowers innovation performance, as firms with higher market

Table 10 Negative binomial regressions (non-linearity analysis)

	(12) Innovation	(13) Innovation	(14) Innovation	(15) Innovation
$INDS_1^2$	3.575***			
	(1.099)			
$INDS_2^2$		5.488*		
		(2.851)		
$CS_1E_i^2$			27.219	
			(35.824)	
$CS_2E_i^2$				1.183
				(1.835)
Firm age	−0.001	−0.001	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Family ownership	−0.344***	−0.393***	−0.423***	−0.415***
	(0.130)	(0.130)	(0.129)	(0.130)
Revenues	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Non-urban	−0.054	−0.087	−0.155	−0.147
	(0.128)	(0.129)	(0.127)	(0.127)
Industry-to-industry	0.515***	0.530***	0.524***	0.512***
	(0.194)	(0.195)	(0.195)	(0.197)
Cluster size	−0.020	−0.012	−0.011	−0.009
	(0.015)	(0.015)	(0.016)	(0.015)
Industry dummies	Yes	Yes	Yes	Yes
Constant	−1.671***	−1.622***	−1.584***	−1.562***
	(0.236)	(0.240)	(0.242)	(0.240)
Sample size	698	698	698	698
McFadden's *R*-squared	0.07	0.06	0.06	0.06

Standard errors are in parenthesis; please note: firm size included as exposure variable

***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 11 Negative binomial regressions (industry-concentration analysis)

	(16) Innovation	(17) Innovation
$Cluster_1$	0.389**	
	(0.164)	
$Cluster_2$		0.130
		(0.290)
HHI	−3.010**	−3.341**
	(1.452)	(1.675)
Firm age	0.000	0.000
	(0.001)	(0.001)
Family ownership	−0.498***	−0.487***
	(0.134)	(0.134)
Revenues	−0.000**	−0.000***
	(0.000)	(0.000)
Non-urban	−0.141	−0.131
	(0.133)	(0.134)
Industry-to-industry	0.409*	0.546***
	(0.217)	(0.210)
Cluster size	−0.024	−0.010
	(0.016)	(0.016)
Industry dummies	Yes	Yes
Constant	−1.341***	−1.392***
	(0.279)	(0.409)
Sample size	641	641
McFadden's R-squared	0.07	0.06

Standard errors are in parenthesis; please note: firm size included as exposure variable

***$p<0.01$, **$p<0.05$, *$p<0.1$

power absorb most of the spillovers. Nevertheless, locating in a cluster is still beneficial in generating an increase in innovation.

5.3 Entropy balancing: control group comparison

In the following, we test the external validity of the relationship in a different context. To do so, we test the generalizability of niche market leaders in Italy.[2] Italy has a similar industry profile to Germany in terms of the key industries of niche market leaders, such as manufacturing, the automotive industry, and construction. That is why Italy serves as a suitable sample setting when studying niche market leaders. The sample of Italian niche market leaders was built in the same way as the German sample, through bottom-up sampling and the evaluation of market registers and local analyses of niche market leaders, such as Southern Tyrol and Lombardy. In total, $N=124$ niche market leaders were identified. In a further step, we compare the sample of Italian niche market leaders with a dataset of $N=1973$ companies from Italy, based on the Italian office of Bureau van Dijk—AIDA, which is considered the standard for firm-level data in Italy (Minichilli et al., 2014). For data availability reasons, we use the Italian setting for the control group analysis. Those companies that serve mass markets and possess the capability for product innovation (top-down sampling) were selected. Therefore, firms, e.g., operating in the public infrastructure, were excluded (Block et al., 2015). Entropy balancing was applied to balance structural differences between the experimental and control groups (Hainmueller, 2012). The matching procedure of firms from both groups was estimated using the first, second, and third moments of covariates based on similarities of firm age and firm size.[3] Thus, the regression models include the weight corrections that were thereby obtained. Table 12 shows the

[2] We use an Italian sample for the control group due to its similar industry profile and a sufficient number of hidden champions. Of course, future research is called to extend our research to further contexts.

[3] To assess the effectiveness of entropy balancing in improving the comparability between the treated and control groups, we compared the key characteristics (firm age and firm size) before and after applying entropy balancing weights to the control group. Before entropy balancing, the mean firm age for the main group was 32.33 years (Std Dev = 18.88), while the control group had a mean of 29.32 years (Std Dev = 19.10). After applying entropy balancing weights, the mean firm age for the control group was adjusted to 32.13 years (Std Dev = 19.90). The difference in mean firm age between the groups decreased from 3.015 to 0.196 years, indicating that the balancing process substantially improved the comparability in terms of firm age. The mean (ln) firm size for the main group was 5.14 (Std Dev = 1.44), compared to 6.32 (Std Dev = 0.72) for the control group before entropy balancing. After weighting, the mean ln (firm size) for the control group was adjusted to 6.01 (Std Dev = 0.40). The difference in mean (ln) firm size between the groups decreased from 1.18 to 0.86, indicating improved balance, although with a reduced standard deviation in the control group, suggesting less variation post-balancing. Overall, entropy balancing effectively improved the comparability between the treated and control groups for firm age and (ln) firm size, thereby enhancing the validity of our comparative analysis.

Table 12 Pooled negative binomial regressions (control group estimation, entropy balancing)

	(18) Innovation	(19) Innovation	(20) Innovation	(21) Innovation
$Cluster_1$	0.737***		0.118	−0.147
	(.265)		(0.123)	(0.114)
Niche market leader		1.474***		1.164***
		(0.132)		(0.201)
Niche market leader × $cluster_1$				0.426**
				(0.216)
Firm age	.016**	0.004	0.006**	0.005**
	(.007)	(.132)	(0.003)	(0.002)
Family ownership	0.237	0.091	0.305***	0.058
	(0.237)	(0.098)	(0.102)	(0.096)
Revenues	0.000**	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Industry-to-industry	2.518***	0.532**	1.395***	0.559**
	(.523)	(.267)	(.222)	(0.277)
Cluster size	−0.018	0.032***	0.013*	0.03***
	(0.022)	(0.008)	(0.008)	(0.008)
Industry dummies	Yes	Yes	Yes	Yes
Constant	−10.099***	−4.998***	−5.251***	−4.921***
	(0.823)	(0.24)	(0.286)	(0.266)
Sample size	455	8233	8233	8233
McFadden's R-squared	0.10	0.09	0.08	0.09

Standard errors are in parenthesis; please note: firm size is included as the exposure variable. This table tests the external validity of the cluster-innovation link using an Italian sample as an alternative national context. Based on a sample of $N = 124$ Italian niche market leaders, the cluster status was calculated as in the main analysis (LQ cut-off). Model 18 presents the results. Models 19 to 21 perform a control group comparison between niche market leaders from Italy and a control group of innovation-capable mass-market firms ($N = 1973$) for the years 2015–2019. Based on the Italian office of Bureau van Dijk (AIDA), a top-down sampling excludes firms from certain industries, such as public infrastructure. The control group comparison is based on entropy balancing. The matching was performed using similarities of firm age and firm size to calculate weights

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

results. The first model uses a sample that only consists of Italian niche market leaders. The effect of the cluster dummy is positive and significant (beta = 0.737***), validating the results from the German sample. The cluster dummy was estimated analogously to the German sample, using the location quotient and a cut-off value of 1.25 (Miller et al., 2001). Models 19 to 21 perform the entropy balancing control group estimation. The data on Italian firms is from 2015 to 2019. Given we assume the absence of individual-specific effects that vary over time, we use pooled negative binomial regression models. Model 19 shows that niche market leaders emulate stronger innovativeness than the control group (beta = 1.474***). Model 20 shows that mass-market firms' inclusion suppresses the positive cluster effect the niche market leaders comprise. Model 21 finally shows that niche market leaders benefit more from locating in a cluster than mass-market firms (beta = 0.426**). This is an interesting finding that underlines the meaning of spatial agglomeration for niche market firms. We conclude that technology specificity as such does not inhibit niche firms from absorbing and using knowledge externalities. In fact, the technology specificity of niche market leaders is likely to especially train their absorptive capacity to a certain extent. The findings of our second hypothesis suggest that a threshold above which specificity exerts an inhibiting effect seems to exist.

6 Conclusions

This research investigates the relevance of spatial agglomeration for the innovation performance of niche global market leaders. We first cluster 1372 German niche market leaders in our main analysis. We identify niche clusters in Germany and document our first hypothesis that (1) locating in a cluster has a positive effect on the innovation performance of niche market leaders. These results are robust using other indicators of spatial agglomeration. We conclude that spillovers are underlying and that niche market firms benefit from spatial proximity. Analyzing various industry levels for our second hypothesis, we find that (2) the effect of cluster location on innovation decreases with technology specificity. Heterogeneous resources within an industry allow the recombining of resources and thus contribute to commercializing knowledge. Moreover, we are able to validate our findings for an Italian sample and build a control-group sample based on entropy balancing. In the comparison, we show that niche market leaders are better able to benefit from locating in a cluster than the mass-market control group, which concerns their innovation output. Thus, technology specificity seems to especially shape and train the absorptive capacity to a certain extent. We assume that only from a certain threshold onwards the effect of specificity exerts a contrary effect.

First, we contribute to a literature that studies external drivers of firm-level innovation. So far, it has paid little attention to niche market leaders and spatial agglomeration. The literature has made great efforts to study knowledge spillovers and clusters for high-tech firms or start-ups, but a potential niche spillover has never been analyzed before. Therefore, we contribute to the understanding of spatial agglomeration for another firm type and inform cluster policies in non-urban areas. Here, we contribute to the literature on industrial clusters and identify niche clusters in Germany. Besides, we draw from the literature on knowledge spillovers and elaborate on how spillovers matter for niche firms. Second, this study contributes to a better understanding of niche market leaders. We extend this literature by addressing the question of whether and to what extent the localization of niche market leaders affects their innovation performance. While most studies on niche market leaders targeted their innovation strategy and compared their output to non-niche SMEs, we shed light on spatial determinants and how they drive innovation. Finally, we contribute to the call for more sector-based entrepreneurship research. In our second hypothesis, we show that the positive effect of locating in a cluster on innovation success is stronger for industry-wise, more heterogeneous clusters. While the technology specificity of niche market leaders seems to help them emulate a strong absorptive capacity (as they outperform the control group), this benefit might come with a threshold.

6.1 Implications for practice

The results of our study have practical implications for firm managers and owners. Our research suggests that clustering can be an important driver of innovation. Considering that knowledge spillovers underly, managers should design their company to strengthen its absorptive capacity. Our data show that proximity is important for innovation, but we also know from the literature that the ability to absorb and process this knowledge is crucial. Our results suggest that firms in the cluster should not close themselves off to remain hidden. Rather, they should interact and cooperate with other firms from similar industries in the cluster. Firm cooperation and knowledge transfer both favor knowledge spillover, which can occur, for example, through labor mobility. Since we see no evidence of non-linearity and possible congestion in the cluster in our data, niche market leaders should not shy away from active exchanges. In highly specific niche markets, the companies are not direct competitors in the output market but instead seem to benefit from knowledge spillovers that they use to develop their specific niche technology.

6.2 Implications for policy-makers

Public policy, on the other hand, needs to put niche market leaders at the top of their agenda to safeguard technology leadership, which is an important driver of exports and economic growth. While niche market leaders are one source of regional development and prosperity (Benz et al., 2021), they are the major pillar in the national Vocational Education and Training system. As clustering is an important determinant of innovation performance, public policy needs to take measures to best equip niche clusters with needed prerequisites. To do so, cluster policies must favor cooperation between companies and encourage proactive exchange. The infrastructure, especially in non-urban areas, must be expanded, and nationwide Vocational Education and Training must be strengthened as a central educational institution. For instance, a culture of technical education must be strengthened to make vocational training attractive and a promising option for studying at colleges and universities.

6.3 Limitations and avenues for future research

Yet, our study comprises some limitations. Our paper investigates the influence of cluster location on innovation performance. The causal link could theoretically be established the other way around, thus implying that niche market leaders choose already established industry clusters as headquarters locations. A possible reverse causality is indeed a common limitation of studies investigating spatial dimensions, which are unable to use historical data (Fritsch & Wyrwich, 2018). However, our sample firms are, on average, 99 years old. Indeed, niche market leaders are commonly founded near the home of the founding family, underlining that reverse causality is rather unlikely. Some examples include Alfred Kärcher (who was born in Bad Cannstatt in 1901 and founded Kärcher in 1935), Apollonia Margarete Steiff (born 1847 in Giengen an der Brenz, founded Steiff in Giengen an der Brienz), Johannes Klais (born in Lüftelberg 1852, founded Klais Orgelbau 18 km away in Bonn, in 1882), and Martin Herrenknecht (born 1942 in Lahr, founded Herrenknecht in 1975 in Lahr and moved it to Schwanau in 1980 for a larger production site, which is only 12 km away). Thus, although we acknowledge the potential reverse causality and bidirectional relationship between location and innovation, we believe that this is an unlikely alternative to explain our findings.

Second, the literature on entrepreneurship and innovation has long discussed the use of patents as a measure. Patents, indeed, do not necessarily measure the innovation performance of companies per se. For instance, it could happen that companies deliberately do not patent in order to make knowledge invisible. Similarly, not every form of innovative knowledge is patentable. Fang (2015) analyzes the type of innovation measurements in her meta-study of cluster-innovation research. The majority of studies (Delgado et al., 2014) clearly use the actual number of innovations or patents as a measurement. The second most common type of measurement is a dummy variable that describes whether companies innovate at all or not. The least used are R&D expenditures, R&D stock, and the number of R&D firms/employees. R&D is indeed a measure of innovation input rather than output. As for that, R&D expenditures are a rather weak measure of innovation performance (Fang, 2015). Even more so, we consider that niche market leaders often deliberately fly under the radar, as Simon (2009) describes. They are rarely listed on the stock exchange, rarely part of well-known political agendas, have a low media presence, and usually have a weak presence on their homepage and on social media. Annual reports are often not published. Getting an accurate listing of actual product and service innovations or R&D data is often very difficult. On the contrary, patents are centrally filed at the national patent office (DMPA in Germany) and are publicly available. Given the otherwise difficult data availability, the use of patents seems like the best solution to measure the innovation performance of niche market leaders.

Third, we focus on the geographic distribution of niche market leaders' headquarters, not including branches and subsidiaries. This approach is valid since agglomeration effects like spillovers occur near the main knowledge source, typically the headquarters. Niche market leaders are highly internationalized, with most subsidiaries located abroad and playing a minor role in their home market. Simon (2009) estimates niche market leaders have an average of 24 subsidiaries, with the majority overseas. Including German subsidiaries would incorrectly assume uniform knowledge distribution, which is unlikely. Thus, we rely on headquarters as they are closest to the primary knowledge source.

Finally, future research could replicate our study for even more economies than only Italy. Different studies on niche market leaders found that they distribute decentralized and unevenly, such as Voudouris et al. (2000) for Greece. Thus, a potential clustering could underlie that, in turn, determines innovative activities. Future research could also look at what differences exist in each niche industry to commercialize external knowledge. An analysis by different niche industries could thus contribute to the literature on knowledge filters and absorptive capacity. The degree of specialization and the type of knowledge itself could explain differences between niche industries.

Moreover, future research could compare the functioning and effectiveness of different types of clusters. Different clusters host different types of firms (start-ups, unicorns, niche market leaders, etc.), and so they differ in the processes of how actors in the clusters interact together. Thus, important conclusions could be drawn for cluster policy (Massard & Autant-Bernard, 2015; Grashof, 2021). Finally, future research should build on our comparison between mass-market and niche-market firms. We found that niche market firms seem to be better able to capitalize on the cluster location than the control group. Future research could thus disentangle the conditions, determinants, and needs of various types of high-tech firm clustering.

Funding Open access funding provided by Università degli studi di Bergamo within the CRUI-CARE Agreement.

Declarations

Competing interests The authors declare no competing interests.

References

Acs, Z. J., Audretsch, D. B., & Feldman, M. P. (1994). R&D spillovers and innovative activity. *Managerial and Decision Economics, 15*(2), 131–138.

Acs, Z. J., Audretsch, D. B., & Feldman, M. P. (1994). R&D spillovers and recipient firm size. *The Review of Economics and Statistics, 76*(2), 336–341.

Acs, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 32*, 15–30.

Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 41*, 757–774.

Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: An empirical analysis. *The American Economic Review*, 678–690.

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica, 60*, 323–351.

Anselin, L., Varga, A., & Acs, Z. J. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics, 42*(3), 422–448.

Arrow, K. (1962). *Economic welfare and the allocation of resources for invention. The rate and direction of inventive activity: Economic and social factors*, pp. 609-626. National Bureau of Economic Research. Princeton University Press: Princeton, New Jersey, USA.

Audretsch, D. B. (1995). *Innovation and industry evolution*. MIT Press: Cambridge.

Audretsch, B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy, 14*(2), 18–29.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review, 86*(3), 630–640.

Audretsch, D. B., & Keilbach, M. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*(7), 1242–1254.

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy, 34*(8), 1191–1202.

Audretsch, D. B., Lehmann, E. E., & Schenkenhofer, J. (2018). Internationalization strategies of hidden champions: Lessons from Germany. *Multinational Business Review, 26*(1), 2–24.

Audretsch, D. B., Belitski, M., & Caiazza, R. (2021). Start-ups, innovation and knowledge spillovers. *The Journal of Technology Transfer, 46*(6), 1995–2016.

Audretsch, D. B., Lehmann, E. E., & Schenkenhofer, J. (2021b). A context-choice model of niche entrepreneurship. *Entrepreneurship Theory & Practice, 45*(5), 1276–1303.

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy, 27*(5), 525–540.

Bell, G. G. (2005). Clusters, networks, and firm innovativeness. *Strategic Management Journal, 26*(3), 287–295.

Benz, L., Block, J. H. & Johann, M. S. (2021). Hidden champions as a determinant of regional development: An analysis of German districts. ZFW–Advances in Economic Geography, https://doi.org/10.1515/zfw-2020-0043.

Block, J. H., Fisch, C. O., Hahn, A., & Sandner, P. G. (2015). Why do SMEs file trademarks? Insights from firms in innovative industries. *Research Policy, 44*(10), 1915–1930.

Brenner, T. (2006). Identification of local industrial clusters in Germany. *Regional Studies, 40*(9), 991–1004.

Cainelli, G., Ganau, R., & Jiang, Y. (2020). Detecting space-time agglomeration processes over the Great Recession using firm-level micro-geographic data. *Journal of Geographical Systems, 22*(4), 419–445.

Chesbrough, H. (2003). The governance and performance of Xerox's technology spin-off companies. *Research Policy, 32*(3), 403–421.

Civera, A., Meoli, M., & Vismara, S. (2019). Do academic spinoffs internationalize? *Journal of Technology Transfer, 44*(2), 381–403.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal, 99*(1), 569–596.

De Massis, A., Audretsch, D. B., Uhlaner, L., & Kammerlander, N. (2018). Innovation with limited resources: Management lessons from the German Mittelstand. *Journal of Product Innovation Management, 35*(1), 125–146.

De Massis, A., Kotlar, J., Wright, M., & Kellermanns, F. W. (2018). Sector-based entrepreneurial capabilities and the promise of sector studies in entrepreneurship. *Entrepreneurship Theory & Practice, 42*(1), 3–23.

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy, 43*(10), 1785–1799.

Döring, T., & Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth? A survey of the literature. *Regional Studies, 40*(3), 375–395.

Fallah, M. H. & S. Ibrahim. (2004). Knowledge spillover and innovation in technological clusters. In: *Proceedings IAMOT 2004 Conference*, Washington DC, 1–16.

Fang, L. (2015). Do clusters encourage innovation? A Meta-Analysis. *Journal of Planning Literature, 30*(3), 239–260.

Feldman, M. P. (1994). *The geography of innovation*. Kluwer Academic.

Feldman, M. P. (2000). Location and innovation: The new economic geography of innovation, spillovers, and agglomeration. In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), *The Oxford handbook of economic geography* (pp. 373–394). Oxford University Press Incorporation.

Fisch, C., Meoli, M., & Vismara, S. (2022). Does blockchain technology democratize entrepreneurial finance? An empirical comparison of ICOs, venture capital, and REITs. *Economics of Innovation and New Technology, 31*(1–2), 70–89.

Fritsch, M., & Wyrwich, M. (2018). Regional knowledge, entrepreneurial culture, and innovative start-ups over time and space - An empirical investigation. *Small Business Economics, 51*(2), 337–353.

Ghio, N., Guerini, M., Lehmann, E. E., & Rossi-Lamastra, C. (2015). The emergence of the knowledge spillover theory of entrepreneurship. *Small Business Economics, 44*, 1–18.

Grashof, N. (2021). Putting the watering can away–Towards a targeted (problem-oriented) cluster policy framework. *Research Policy, 50*(9), 104335.

Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics, 10*(1), 92–116.

Grossman, G. M., & Helpman, E. (1994). Endogenous innovation in the theory of growth. *Journal of Economic Perspectives, 8*(1), 23–44.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis, 20*(1), 25–46.

Hollander, H. (2020). *Methodology report for the European panorama of clusters and industrial change and European cluster database*. European Commission Publications Office.

Jacobs, J. (1969). *The economy of cities*. Jonathan Cape.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. *The American Economic Review, 76*(5), 984–999.

Kirschning, R., & Mrożewski, M. (2023). The role of entrepreneurial absorptive capacity for knowledge spillover entrepreneurship. *Small Business Economics, 60*(1), 105–120.

Lehmann, E. E., Schenkenhofer, J., & Wirsching, K. (2019). Hidden champions and unicorns: A question of the context of human capital investment. *Small Business Economics, 52*, 359–374.

Lorenzo, D., Núñez-Cacho, P., Akhter, N., & Chirico, F. (2022). Why are some family firms not innovative?: Innovation barriers and path dependence in family firms. *Scandinavian Journal of Management, 38*(1), 101182.

Love, J. H., Roper, S., & Vahter, P. (2014). Learning from openness: The dynamics of breadth in external innovation linkages. *Strategic Management Journal, 35*(11), 1703–1716.

Marshall, A. (1890). *Principles of economics*. Macmillan.

Massard, N., & Autant-Bernard, C. (2015). Geography of innovation: New trends and implications for public policy renewal. *Regional Studies, 49*(11), 1767–1771.

Maurseth, P. B., & Verspagen, B. (2002). Knowledge spillovers in Europe: A patent citations analysis. *The Scandinavian Journal of Economics, 104*(4), 531–546.

Miller, P., Botham, R., Martin, R., & Moore, B. (2001). Business clusters in the UK: A first assessment. *Department of Trade and Industry, London, 3*(2), 18–32.

Minichilli, A., Nordqvist, M., Corbetta, G., & Amore, M. D. (2014). CEO succession mechanisms, organizational context, and performance: A socio-emotional wealth perspective on family-controlled firms. *Journal of Management Studies, 51*(7), 1153–1179.

Nieto, M., & Quevedo, P. (2005). Absorptive capacity, technological opportunity, knowledge spillovers, and innovative effort. *Technovation, 25*(10), 1141–1157.

Ottosson, M., & Kindström, D. (2016). Exploring proactive niche market strategies in the steel industry: Activities and implications. *Industrial Marketing Management, 55*(1), 119–130.

Paci, R., & Usai, S. (1999). Externalities, knowledge spillovers, and the spatial distribution of innovation. *GeoJournal, 49*(4), 381–390.

Pahnke, A., & Welter, F. (2019). The German mittelstand: Antithesis to silicon valley entrepreneurship? *Small Business Economics, 52*(1), 345–358.

Parrish, E. D., Cassill, N. L., & Oxenham, W. (2006). Niche market strategy for a mature marketplace. *Marketing Intelligence & Planning, 24*(7), 694–707.

Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review, 76*(6), 77–90.

Pouder, R., & St John, C. H. (1996). Hot spots and blind spots: Geographical clusters of firms and innovation. *Academy of Management Review, 21*(4), 1192–1225.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002–1037.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5), 71–102.
Sammarra, A., & Biggiero, L. (2008). Heterogeneity and specificity of inter-firm knowledge flows in innovation networks. *Journal of Management Studies, 45*(4), 800–829.
Schenkenhofer, J. (2022). Hidden champions: A review of the literature & future research avenues. *Management Review Quarterly, 72*(2), 417–482.
Schmid, S., & Welter, F. (2024). In danger of being left behind?–Media narratives of the digital transformation in the German Mittelstand. *Entrepreneurship & Regional Development, 36*(1–2), 98–114.
Schumpeter, J. A. (1934). *The theory of economic development*. Harvard University Press.
Sharma, P., Chrisman, J. J., & Chua, J. H. (1997). Strategic management of the family business: Past research and future challenges. *Family Business Review, 10*(1), 1–35.
Simon, H. (2009). *Hidden champions of the twenty-first century. Success Strategies of Unknown World Market Leaders*. Springer eBook Collection Business and Economics. Springer: New York, NY.
Sternberg, R., & Litzenberger, T. (2004). Regional clusters in Germany-Their geography and their relevance for entrepreneurial activities. *European Planning Studies, 12*(6), 767–791.
Toften, K., & Hammervoll, T. (2013). Niche marketing research: Status and challenges. *Marketing Intelligence & Planning, 31*(3), 272–285.
Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory & Practice, 42*(3), 467–497.
Voudouris, I., Lioukas, S., Makridakis, S., & Spanos, Y. (2000). Greek hidden champions. *European Management Journal, 18*(6), 663–674.
Wang, L., & Tan, J. (2019). Social structure of regional entrepreneurship: The impacts of collective action of incumbents on de novo entrants. *Entrepreneurship Theory & Practice, 43*(5), 855–879.
Wennberg, K., & Lindqvist, G. (2010). The effect of clusters on the survival and performance of new firms. *Small Business Economics, 34*(3), 221–241.
Wennberg, K., Wiklund, J., & Wright, M. (2011). The effectiveness of university knowledge spillovers: Performance differences between university spinoffs and corporate spinoffs. *Research Policy, 40*(8), 1128–1143.