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Nils Grashof

Utrecht University Human Geography and Planning

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Nils Grashof

Centre for Regional and Innovation Economics, University of Bremen, Germany

Max-von-Laue-Str. 1, 28359 Bremen, Tel.: +49-421 218-66536, E-Mail: NGrashof@uni-bremen.de

Abstract

Regional clusters have become an inseparable component of modern economies. Spurred by the idea that clusters unrestrictedly encourage firm innovativeness, such as in the lighthouse example of Silicon Valley, the cluster approach has particularly gained attention among policy makers who have supported the creation and development of clusters. Nevertheless, due to a lack of holistic consideration of different influencing variables, the scientific results about the effect of clusters on firm innovative performance are highly contradictive. For companies as well as policy makers, it is therefore still difficult to evaluate the concrete consequences of being located in a cluster. Consequently, the aim of this paper is to empirically investigate the conditions and mechanisms through which companies can gain from being located in clusters, focussing thereby in particular on possible knowledge spillovers. Therefore, based on an integration of the theoretical perspectives from the strategic management (e.g. resource-based view) and the economic geography literature (e.g. cluster approach), variables from three different levels of analysis (micro-level, meso-level and macro-level) are considered separately as well as interactively. By analysing a unique multilevel dataset of 11,889 companies in Germany, including 1,391 firms that are located within a cluster, evidence is found that being located in a cluster has indeed a positive impact on firm innovative performance. However, the results also indicate that firms benefit unequally within the cluster environment, depending on the specific firm, cluster and market/industry conditions.

Keywords: knowledge spillovers, cluster effect, firm performance, multilevel analysis, innovation
JEL Codes: C31, L10, L22, O30, R10

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1. Introduction

The geographical concentration of economic activities forms an elementary component of today´s economic reality (Brown et al., 2007; Nathan and Overman, 2013). As such, regional clusters have gained considerable attention among scientists as well as policy makers (Martin and Sunley, 2003; Sedita et al., 2012). Inspired by early theoretical contributions about clusters and lighthouse case studies, such as Silicon Valley, the idea that clusters promote innovativeness and productivity has settled in the heads, particularly, of policy makers. By pursuing the goal of writing a similar success story for their region, policy makers at all levels of governance have implemented measures to create or support clusters (Festing et al., 2012; Martin et al., 2011; Terstriep and Lüthje, 2018). Most European countries have therefore already realized national and regional cluster programs (European Union, 2016; Zenker et al., 2019). For example, since 2005 the German national government has launched several programs with a total volume of 1,391 billion € to foster excellent clusters in Germany (EFI, 2015; Festing et al., 2012).[1]

Despite the already substantial financial support of cluster activities, an invariably positive effect of clusters on firm performance is still not conclusively proven. Instead, the scientific results about the firm-specific cluster effect are indeed highly contradictive (Malmberg and Maskell, 2002; Martin and Sunley, 2003). Some studies have found empirical evidence for a positive performance effect (Baptista and Swann, 1998; Bell, 2005), while others have also emphasized rather mixed (Knoben et al., 2015) or even negative performance effects (Pouder and St. John, 1996).

Apart from the lack of standardized methodologies and cluster definitions, this inconsistency can mainly be explained by the missing systematic consideration of potential moderating variables. Among scientists in this field, it is actually quite prevalent to assume that all companies profit equally and in the same manner from being located in a cluster (Frenken et al., 2013; Šarić, 2012; Tallman et al., 2004). Even Michael Porter assumes that "a vibrant cluster can help **any** company in **any** industry compete in the most sophisticated ways, using the most advanced, relevant skills and technologies." (Porter, 1998, p. 86). Nevertheless, by just having a short and superficial look at the broad field of studies dealing with firm performance differentials, it becomes obvious that this idea is rather questionable (Dyer and Singh, 1998; Van Oort et al., 2012; Vega-Jurado et al., 2008). In this context, a comprehensive meta-analysis from 2017 of the cluster literature identified several moderating variables, such as the industry context (Grashof and Fornahl, 2020).

[1] A comprehensive overview about the financial budgets of different cluster programs in Europe is provided by Zenker et al. (2019).

Frenken et al. (2013) therefore make a call to “open the black box” (Frenken et al., 2013, p. 23) about the conditions and mechanisms through which the firm-specific advantages of localization economies, including for instance the benefits of specialized labour markets, specialized inputs and knowledge spillovers (e.g. Marshall, 1920), can be realized. The aim of this paper is to respond to this call for the Marshallian component of knowledge spillovers by answering the following research question: Under which conditions can a company located in a cluster profit from knowledge spillovers?

While this firm-specific perspective has been widely ignored in the previous cluster research, there are some important exceptions (Brown et al., 2007; Grillitsch and Nilsson, 2017; Šarić, 2012; Steffen, 2012; Van Oort et al., 2012). However, these relatively recent articles again come to contradictory empirical results (Grillitsch and Nilsson, 2017; Hervas-Oliver et al., 2018). On the one hand, evidence is found that knowledge-poor firms gain the most from being located in a cluster (Rigby and Brown, 2015; Shaver and Flyer, 2000). But on the other hand, some studies highlight that knowledge-rich firms are the main beneficiaries (McCann and Folta, 2011). Consequently, it is reasonable to assume that additional moderating variables must be taken into consideration in order to analyse the relationship between clusters and firm performance in a more sophisticated way.

To do so, based on a theoretical integration of the resource-based view, the relational view, the market-based view and the cluster approach, this paper investigates three different levels of analysis (micro-level, meso-level, and macro-level) by applying an OLS regression with clustered standard errors of single cross-sectional averages over time. Therefore, varying data sources are applied, ranging from firm-level to market and industry-level data. The chosen methodical approach is appropriate as it takes the hierarchical data structure, the corresponding context dependency and the year-to-year variability being ubiquitous in micro-level data into account (McNeish, 2014; Moulton, 1990; Rigby and Brown, 2015).

By providing an answer to the underlying research question, the paper not only contributes to closing a still ubiquitous research gap but also has a pragmatic meaning, because companies as well as policy makers can evaluate better under which conditions it is more likely to realize a competitive advantage in clusters or in other words a firm-specific cluster advantage.

The remainder of this paper is structured as follows: The second section introduces the theoretical background, highlighting the theoretical debate about knowledge spillovers, establishing an adequate working definition of a cluster and elaborating the corresponding hypotheses. In the third section, the applied methodical approach and data is described in detail. Thereafter, the fourth section presents the empirical results. The paper will end with some concluding remarks, including limitations to this study as well as promising future research directions.

2. Theoretical foundation of the cluster and firm performance relationship

Although the term cluster is a very widespread and prevalent theme in economics, at least since the two scientific papers of Porter (1990 and 1998), there are still fundamental differences in its definition as well as understanding (Brown et al., 2007; Malmberg and Maskell, 2002; Martin and Sunley, 2003). Even Silicon Valley, which is one of the most prominent case studies in the literature, has already been defined as a regional network, industrial district, innovative milieu, agglomeration and learning region, among others (Šarić, 2012). As a consequence of the unclear definitional delimitation, the term has experienced a large proliferation and thereby has lost some of its explanatory power (Brown et al., 2007; Martin and Sunley, 2003; Šarić, 2012; Sedita et al., 2012). This study does, however, not intend to open a theoretical discussion about a new (conceptual) cluster definition. Instead, the following working definition of a cluster, derived through a comparative empirical approach in Grashof and Fornahl (2020), is used: "Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market." (Grashof and Fornahl, 2020, p. 10f.). Moreover, in line with several authors (Delgado et al., 2010; Martin et al., 2011; McCann and Folta, 2011) the terms cluster and agglomeration are used interchangeably.

Marshall (1920) was actually among the first to consider the benefits that firms can gain from being located in close proximity to firms from the same industry. He presented in this context four types of agglomeration externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing consumer search costs (Marshall, 1920; McCann and Folta, 2008).[2]

The focus of this paper lies on knowledge spillovers. A view held by many economists is that geographic proximity can facilitate the transfer of knowledge in general (Jaffe et al., 1993) and the transfer of tacit knowledge specifically because it increases the likelihood of face-to-face contacts, which is an efficient medium for the transfer of such knowledge (Daft and Lengel, 1986). Generally, it can be differentiated between formal linkages such as licensing,

[2] Besides these externalities he also noted that the unique physical conditions of particular areas, such as limited natural resources, are the chief cause for the localization of industries.

technology partnerships as well as strategic alliances and informal linkages through which the transfer of tacit knowledge can be simplified (McCann and Folta, 2011; Pouder and St. John, 1996). Apart from geographic proximity, it has been pointed out that additional types of proximity capturing cognitive, organizational, social or institutional characteristics can also foster knowledge diffusion (Boschma, 2005). However, it has been emphasized that these types of proximity are highly interrelated. In other words, there is a greater likelihood that actors which are co-located in close distance hold the same norms, share the same culture and follow the same regulations (Grillitsch and Nilsson, 2017). Even though not in the centre of the current scientific discussion, negative knowledge spillovers may also be the result of being located in close proximity to similar firms, in the sense that knowledge leakages are more likely to happen in an environment of reinforced knowledge exchange (Grillitsch and Nilsson, 2017; Shaver and Flyer, 2000). Additionally, some authors suggest that a simple reliance on local face-to-face contacts and tacit knowledge makes local networks of industry especially vulnerable to lock-in situations, which in turn enforce the inertia of companies within clusters (Boschma, 2005; Martin and Sunley, 2003). In this context, Pouder and St. John (1996) argued that the firm performance decline over time can be explained with the convergent mental models of managers within the corresponding region. As a consequence of this kind of uniform thinking, a sort of group thinking comportment, old behaviours as well as old ways of thinking are reinforced which prevent the recognition and adoption of new ideas.

While the reviewed theory about knowledge spillovers is in general rather uncontroversial in its tenor about the possible (dis-)advantages of being located in a cluster, the literature is nearly silent about the concrete conditions through which those outcomes can be realized (Frenken et al., 2013; McCann and Folta, 2011).

2.1. Firm-level conditions (Micro-level)

This silence is particularly astonishing in light of the resource-based view (RBV). The resource-based view of the firm is regarded as one of the most widely accepted theoretical perspectives in the field of strategic management (Newbert, 2007; Steffen, 2012). But it has also been conceptually extended towards the regional or the cluster level (Hervas-Oliver and Albors-Garrigos, 2007; Hervas-Oliver and Albors-Garrigos, 2009). The RBV emerged from the contributions of Penrose (1959), Rubin (1973) and Wernerfelt (1984), who claimed that firms have to be seen as resource bundles. Since then the RBV has continuously been further elaborated.[3] Its focus lies on firms' internal resource bases and how firms can utilize these resources in order to gain a competitive advantage. The strength of firms' resources depends

[3] For a good overview see for example Newbert (2007). The Knowledge-based view can be additionally seen as one specific shaping of the RBV (Grant, 1996).

on their characteristics, namely whether they are valuable, rare, non-substitutable and imitable (Barney, 1991; Newbert, 2007; Steffen, 2012). In accordance with Barney (1991), resources are here defined as “all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness.” (Barney, 1991, p. 101). The underlying assumptions of the RBV are resource immobility and heterogeneity between companies. Both assumptions are necessary for the existence of different resource endowments and its persistency over time (Barney, 1991; Newbert, 2007). Regarding knowledge spillovers it has been argued that firms own different innovation capabilities to actually profit from these externalities (Hervas-Oliver and Albors-Garrigos, 2009; Hervas-Oliver et al., 2018; McCann and Folta, 2011). Cohen and Levinthal (1990) established in this context the term absorptive capacity[4], which describes not only a firm´s ability to recognize and evaluate new information from its environment but also its ability to process it and finally integrate it into the corresponding business innovation activities (Cohen and Levinthal, 1990).

In accordance with the core idea of the RBV, there is empirical evidence that firms with higher innovation capabilities benefit more form available knowledge spillovers. By having higher innovation capabilities, companies are better capable of accessing and integrating external knowledge (Knoben et al., 2015; McCann and Folta, 2011). Although these results are quite in line with the core idea of the RBV, they neglect to some extent that strong internal innovation capabilities also implicate a higher amount of unintentional knowledge spillovers to possible competitors. These outflows of knowledge are claimed to reduce continuously a firm´s relative competitive advantage over other firms (Hervas-Oliver et al., 2017; Knoben et al., 2015; Shaver and Flyer, 2000). Thus, the following hypothesis is proposed:

Hypothesis 1a: The strength of the innovation capabilities of a firm has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with moderately strong innovation capabilities.

In this context, it has additionally been emphasized that the capacity of firms to absorb and process new knowledge efficiently requires cognitive proximity. This means that it is essential to own a knowledge base that is close enough to the new knowledge so that the corresponding company can actually understand and evaluate the new knowledge in a resource-efficient way (Boschma, 2005; Nooteboom, 2000). While a certain level of cognitive proximity is required to gain from knowledge spillovers, too much cognitive proximity might be, however, detrimental

[4] In accordance with Hervas-Oliver et al. (2018), the terms absorptive capacity and innovation capability are used interchangeably.

to firm innovativeness. A high level of cognitive proximity between two actors decreases, for example, the potential of learning something radically new. Furthermore, it also increases the likelihood of a lock-in situation as well as the possibility of negative knowledge spillovers (Boschma, 2005; Fornahl et al., 2011). A moderate level of cognitive proximity is therefore likely to be most beneficial for firms (Boschma, 2005; Boschma and Frenken, 2010; Nooteboom, 2000). While the effect of cognitive proximity has been analysed extensively on the actors' level (e.g. Broekel and Boschma, 2012; Fornahl et al., 2011), the cognitive proximity between the firm´s knowledge stock and the overall stock of knowledge within the corresponding cluster has not been investigated yet. In line with the call for further investigation of this aspect by McCann and Folta (2008) as well as in accordance with Nooteboom (2000), the following hypothesis is proposed:

Hypothesis 1b: The cognitive proximity between the firm´s knowledge stock and the overall stock of knowledge of the corresponding cluster has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with a moderate level of cognitive proximity.

In light of the increasing significance and proliferation of inter-firm alliances, an extension of the RBV called the relational view (RV) has been developed since the late 1990s (Hervas-Oliver and Albors-Garrigos, 2009; Lavie, 2006; Steffen, 2012). While the RBV has only considered those resources and capabilities that are housed within the firm, the RV focuses on inter-firm relationships and routines as valuable resources. Firms' critical resources may extend beyond firm boundaries. As a consequence, for the realization of a competitive advantage, it is not sufficient to only focus on the internal resources, but additionally it is crucial to consider relational resources (Dyer and Singh, 1998; Lavie, 2006). This relational dimension among economic actors has also been increasingly analysed by economic geographers as well as in the context of clusters (Giuliani, 2007; Wu et al., 2010). Within clusters, a firm can have various kinds of linkages. In correspondence with the relational view, it is emphasized that the extent of strategic relationships is positively associated with firm performance (Hervas-Oliver and Albors-Garrigos, 2009). Maintaining a relatively high share of local connections (within the cluster) can allow firms to extract more external knowledge from their environment, which in turn makes it more likely that firms can gain from possible knowledge spillovers. Apart from local relationships, it is additionally useful for companies to have external connections with more distant partners. Thereby, companies may acquire access to an additional knowledge base which is different from the knowledge of local partners (Knoben et al., 2015; McCann and Folta, 2011; Zaheer and George, 2004). Thus, the following hypothesis is proposed:

Hypothesis 1c: The number of linkages of a firm has a positive effect on firm innovative performance in clusters.

Nevertheless, as described by Dyer and Singh (1998), relation-specific resources and capabilities, such as the ability to identify and evaluate potential complementarities, have to be devoted to each collaborative relationship in order to maximize the relational rents[5] (Dyer and Singh, 1998). The availability of these resources and capabilities is, however, limited. Consequently, the higher the share of local connections, the less relation specific resources and capabilities can be used for establishing and/or maintaining relationships with organizations outside the cluster. The absence of outside relationships can in turn lead to lock-in situations in which companies are unresponsive to external changes (Hervas-Oliver and Albors-Garrigos, 2009; Knoben et al., 2015). Based on these arguments, the following hypothesis is proposed:

Hypothesis 1d: The level of local (external) connectedness has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with a moderate share of local (external) connections.

Besides the level of firm connectedness, it has been highlighted, especially in the network literature, that the firm´s network position can also influence the performance (Ferriani and MacMillan, 2017; Zaheer and Bell, 2005). Companies that are central actors within the network or the cluster are less likely than peripheral firms to miss valuable information. Moreover, by occupying a superior network position, companies are supposed to verify better the quality of the received information as well as the trustworthiness of the corresponding exchange partners. This can be crucial, as it is indicated that due to, among others, strategic reasons an exchange partner may limit the provided information (Bell, 2005; Zaheer and Bell, 2005). Thus, the following hypothesis is proposed:

Hypothesis 1e: The centrality of a firm´s cluster position has a positive effect on firm innovative performance in clusters.

[5] According to Dyer and Singh (1998) relational rents are defined as: "(…) supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation and can only be created through the joint idiosyncratic contributions of the specific alliance partners." (Dyer and Singh, 1998, p. 662).

2.2. Cluster-level conditions (Meso-level)

In contrast to other studies, this paper addresses the firm-specific cluster effect in a novel way, namely by analysing, in addition to the micro-level perspective, the specific cluster attributes which can also influence firm innovative performance within clusters.[6] Likewise, in the case of the differences in the resource endowments on the firm-level emphasized by the RBV (e.g. Barney, 1991), it is therefore essential to also consider the heterogeneity on the cluster-level (Hervas-Oliver and Albors-Garrigos, 2007). In this context, one very interesting point to look at is the differences in the stock of knowledge across clusters (McCann and Folta, 2008). As highlighted at the beginning of this section, knowledge spillovers are likely to happen in all clusters; however, it has been emphasized that they are likely to generate larger performance effects in clusters with a relatively high knowledge stock (Beaudry and Breschi, 2003; Knoben et al., 2015; McCann and Folta, 2008). Thus, the following hypothesis is proposed:

Hypothesis 2a: The stock of knowledge of the cluster has a positive effect on firm innovative performance in clusters.

Another relevant cluster-level attribute is the stock of alliances within the cluster (McCann and Folta, 2008). Similar to hypothesis 1c and in line with the core idea of the RV highlighting the importance of relational resources (e.g. Dyer and Singh, 1998), it is expected that within alliance-rich clusters, the possibility to extract knowledge from local and external connections is enhanced. In this way, it should be much easier in an alliance-rich cluster for companies to come in contact with a larger number of different partners than in an alliance-poor cluster. Thus, the following hypothesis is proposed:

Hypothesis 2b: The stock of alliances of the cluster has a positive effect on firm innovative performance in clusters.

The participation and support of local organizations within the cluster, such as technical assistance centres, can additionally influence firm innovative performance. Research institutes, for example, can be instrumental in bringing different firms together to cooperate. Moreover, they are conducive for the generation and diffusion of knowledge within the corresponding cluster (Hervas-Oliver and Albors-Garrigos, 2007; Molina-Morales and Martínez-Fernández, 2004; Wu et al., 2010). Thus, the following hypothesis is proposed:

Hypothesis 2c: The participation and support of local research institutes have a positive effect on firm innovative performance in clusters.

[6] Important exceptions in this context are Knoben et al. (2015) as well as Rigby and Brown (2015).

2.3. Market-/Industry-level conditions (Macro-level)

Alongside these two different levels of analysis, the effect of the market and industry environment on firm performance has been widely acknowledged (Kohlbacher et al., 2013). One of the most prominent theoretical streams in this context is the market-based view (MBV), which is predominantly influenced by the earlier work of Michael Porter (Porter, 1980; Steffen, 2012). In line with the MBV and building on the two scientific papers of Suarez and Lanzolla (2005 and 2007), dealing with external influences on the first-mover advantage, it is supposed that the pace of technology evolution affects firm innovative performance in clusters (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). New product categories may experience very different paces of technology evolution. For example, while the degree of efficiency improvements over time for the computer industry is very high, it is only marginal for vacuum cleaners. The pace of technology evolution can be captured through the technology S-curve which depicts the evolution of a technology along a particular performance parameter, such as the CPU clock speed in the case of the computer industry (Cooper and Schendel, 1976; Suarez and Lanzolla, 2007). Under a rapid or radical technology evolution, it is likely that the current knowledge stock of firms as well as clusters becomes rather unsuitable or even obsolete. In addition, such a technological evolution will increase the market risk. This in turn has again a rather negative effect, as it is expected that under a high market risk, companies will exchange less knowledge as well as invest fewer resources and capabilities in new relationships, reducing the potential benefits from being located in close proximity to similar firms (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Thus, the following hypothesis is proposed:

Hypothesis 3a: The pace of technology evolution has a negative effect on firm innovative performance in clusters.

Furthermore, it is assumed that the extent to which a firm conducts the underlying activities of research and development (R&D), namely basic research, applied research or experimental development, can also moderate the contribution of knowledge spillovers to the realization of a firm-specific cluster advantage. In contrast to applied research and experimental development being more commercially oriented (Czarnitzki and Thorwarth, 2012), basic research is defined as "(…) experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view." (OECD, 2002, p. 77). In other words, basic research is never some final product, but instead it refers to new knowledge that is potentially applicable in different contexts. Conducting basic research therefore provides protection against the introduction of an innovation from an unexpected (technological) direction, as companies become better capable of understanding and monitoring potential new trends as well as possible threats by competitors (Czarnitzki and Thorwarth, 2012; Rosenberg, 1990). Since clusters seem to be a preferable environment for radical innovations (e.g. Grashof et al., 2019), potentially leading to the formation of completely new markets and industries (e.g. Cooper and Schendel, 1976; Henderson and Clark, 1990; Verhoeven et al., 2016), this kind of protection through basic research appears to be especially important for firms located in clusters. Besides, companies may additionally benefit from first-mover advantages, as they can gain from learning experiences as well as acquire assets, such as limited natural resources, which create entry barriers for competitors (Rosenberg, 1990). This in turn creates a competitive advantage for subsequent applied research and development, which is assumed to be of particular importance in a highly competitive setting such as a cluster. Thus, the following hypothesis is proposed:

Hypothesis 3b: The share of basic research of overall R&D activities has a positive effect on firm innovative performance in clusters.

As already highlighted at the beginning, the overall aim of this paper is to reduce the ambiguity surrounding the cluster and firm performance relationship. Therefore, the assumed effects are not just analysed separately, but also simultaneously. By taking the firm-level, cluster-level and market-/industry-level heterogeneity simultaneously into account and focussing on the interactions between these three levels of analysis, the firm performance differentials within clusters can be explained from a broader perspective.

3. Data and Methodology

In order to do so, this paper employs various data sources and variables for each level of analysis.

Micro-level. The main database for the analysis of the innovative performance of companies within clusters is an extensive firm-level database provided by the Stifterverband. This database, which is based on a large survey taking place in a two-year rhythm, is primarily created for the use of the Federal Ministry of Education and Research in Germany. It contains innovation-related information on all identified R&D-active firms in Germany between 1995 and 2015 (Engel et al., 2016; Stifterverband, 2018). Building on this database, the dependent variable for firm innovativeness can be calculated. Innovativeness is measured by the average share of the firm´s product innovations between 1997 and 2013, including incremental as well as new to the market/firm innovations, in previous three years sales (Delgado, 2018; Steinberg et al., 2017). This indicator offers two main advantages over using patents as proxy for firm innovativeness. First, the innovative output of companies that do not patent their product innovations can also be considered. Furthermore, the share of the firm´s product innovations in sales is a market-driven indicator for innovation. Consequently, unlike in the case of patents, the true economic value of the corresponding innovation can be elaborated (Delgado, 2018; Dziallas and Blind, 2019; Kleinknecht et al., 2002). Therefore, it is argued that the share of the firm´s product innovations in sales is more appropriate to measure firm innovativeness than patents for the purpose of this study.

As already highlighted in the previous theoretical discussion, the innovation capabilities of a firm are used as an independent variable but are measured in a twofold way. Like in previous research (e.g. Knoben et al., 2015; Smit et al., 2015), the quantitative aspect of innovation capabilities is calculated by the average share of R&D employees on the total number of employees between 1997 and 2015. In line with the indication by McCann and Folta (2008) as well as Fornahl et al. (2011), the qualitative aspect of innovation capabilities is additionally considered. Therefore, the cognitive proximity as the degree of overlap between the cluster and the firm´s knowledge base is calculated. The database from the Stifterverband once again provides the basis for defining the similarity between the cluster and the corresponding company. To create an average knowledge profile for each company, the internal R&D spending for each product category based on the statistical classification of products by activity in the European Economic Community is employed for the time period between 2005 and 2013. The average of all firms knowledge profiles located in one specific cluster is used to identify the knowledge profile of the corresponding cluster. To finally measure the similarity, the Cosine index is estimated.

$$similarity = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{1.}$$

The cosine index measures the similarity between the two vectors A (firm´s knowledge profile) and B (cluster knowledge profile) for n product categories. In total, 50 different product categories are taken into consideration. The index can take a value between zero and one, where one means perfect similarity between both knowledge profiles.

This paper utilizes data about subsidized R&D collaborations from the German subsidy catalogue ("Förderkatalog") for the relation- and network-specific variables. The database consists of approximately more than 160,000 running or completed R&D projects subsidized by six different ministries[7] in the time span between 1960 and 2016 (Roesler and Broekel, 2017). It has been already frequently used to model knowledge networks and it provides information at an earlier stage compared to patent data (Broekel, 2015; Broekel and Graf, 2012). To gain a preferably comprehensive picture about the firm-specific relationships, the number of linkages of a firm is calculated based on all corresponding collaborative R&D projects between 2005 and 2015. For the measurement of the level of local and extra connectedness, it is essential to make use of the cluster identification (explained in detail on the next page), which serves as the frontier between both forms of connectedness. The level of local (external) connectedness is calculated by the share of cluster internal (external) relations in the total number of linkages.

Various indicators can represent the firm´s network position (Broekel and Graf, 2012; Lechner and Leyronas, 2012; Zaheer and Bell, 2005). In this article, the actor-based cluster index by Brenner (2017), which will be described in detail in the context of the cluster identification, is applied. Besides the identification of clusters, this index offers information about the position of each actor within a cluster by considering the spatial concentration and the geographical distance on the firm-level. It can therefore also be used to determine the firm´s position within a cluster. High values indicate that companies are located in the centre of a cluster, whereas low values show that they are far away from clusters (Brenner, 2017; Scholl and Brenner, 2016). For the firm´s centrality within the corresponding cluster core, a dummy variable is calculated based on the above median of the cluster index (equal to a value of 2.83).[8]

Meso-level. The databases from the Stifterverband as well as the “Förderkatalog” are also the basis for some of the variables on the meso-level. The stock of knowledge across clusters is measured by the average share of R&D employees of all firms of one specific cluster.

The stock of alliances within the clusters is determined in a similar way. By aggregating all firm-specific relationships in one cluster and then dividing it by the number of firms in the corresponding cluster, an indicator can be derived which proxies adequately the stock of alliances within the clusters.

Furthermore, the participation and support of local organizations is measured by the number of research institutes within a cluster for the year 2015.[9] Hereby, the German research directory (“Research Explorer”) is employed. This database contains information on over 25,000 university and non-university research institutes in Germany (Research Explorer, 2018). For the final analysis, however, only the highest organizational level of the research institutes, e.g.

[7] More specifically, these ministries are the Federal Ministry of Education and Research (BMBF), Federal Ministry for Economic Affairs (BMWi), Federal Ministry for Environment, Nature Conservation and Nuclear Safety (BMU), Federal Ministry of Transport, Building and Urban Development (BMVBS), the Federal Ministry of Food, Agriculture (BMEL) and Consumer Protection.
[8] As a first robustness check, the cluster index has also been directly tested as a metric variable. The results thereby remain the same and can be provided upon request.
[9] Due to data constraints, the average number of research institutes within clusters could not be calculated for a longer time period.

universities and not their working groups, are considered.

Macro-level. Patents, retrieved from the database PATSTAT, are used to calculate the pace of technology evolution. In order to determine a trend and to control for possible outliers, the average technological improvement in three-digit NACE Rev. 2 code industries is computed for a two-year period (2012-2013). The average technological improvement is then weighted by the size of the corresponding industry, measured by the average number of employees. Despite well-discussed drawbacks, patents are widely accepted to be an adequate proxy for the technological advances in industries (Haupt et al., 2007; McGahan and Silverman, 2001). For the measurement of the underlying activities of R&D, the database from the Stifterverband is used, as it offers information about the share of internal R&D expenditures on basic research, applied research or experimental development. To exploit the panel structure of the database, the corresponding average share of internal R&D expenditures for the three types of activities are calculated for the time period between 2001 and 2015.

Cluster identification. As the main analysis focuses only on companies within clusters, it is crucial to determine these regional clusters correctly. To identify all relevant clusters in Germany, the method by Brenner (2017) is applied by calculating a cluster index for each single firm on the community level ("Gemeindeebene") based on official employment data from 2012 in three-digit NACE Rev. 2 industries.[10] In general, the actor-based cluster identification by Brenner (2017) has two main advantages over more traditional indicators such as a regional specialization quotient (e.g. Hervas-Oliver et al., 2018; Sternberg and Litzenberger, 2004). First, it avoids the Modifiable Area Unit Problem (MAUP), because it is free of predefined borders (for an exemplary illustration see figure 1). Consequently, in contrast to all other approaches, the results of this cluster identification do not depend on the regional level that is used. As already highlighted, the corresponding cluster index can additionally be used to distinguish between the core and the periphery of a cluster. Second, it avoids a possible overvaluation of one very large company in the regional employment structure, such as Volkswagen (VW) in Wolfsburg, by considering the distance to all other firms of the same industry as a weight to the final cluster index. Therefore, large but geographical isolated firms are in this sense not part of a regional cluster. The applied distance decay function is thereby based on travel times, where 45 minutes represent the limit for close geographical distance (Brenner, 2017; Scholl and Brenner, 2016). Besides the geographical distance, the index also considers employment in absolute terms, capturing the concentration aspect of clusters, as well as in relative terms, referring to specialization. The used cluster index therefore

[10] In line with other studies (e.g. Maggioni, 2002), the three-digit NACE code is argued to be the most adequate level of analysis, as it is not too broad (as the two-digit codes) nor too detailed (as the four-digit codes). It therefore fits perfectly the purpose to identify firms that are located in a cluster.

corresponds adequately to the most central elements of cluster definitions (Grashof and Fornahl, 2020). In line with the procedure of the European Cluster Observatory, a value of 2 is applied as the corresponding cluster threshold, indicating whether a firm is located in a cluster or not (European Cluster Observatory, 2018; European Commission, 2008).

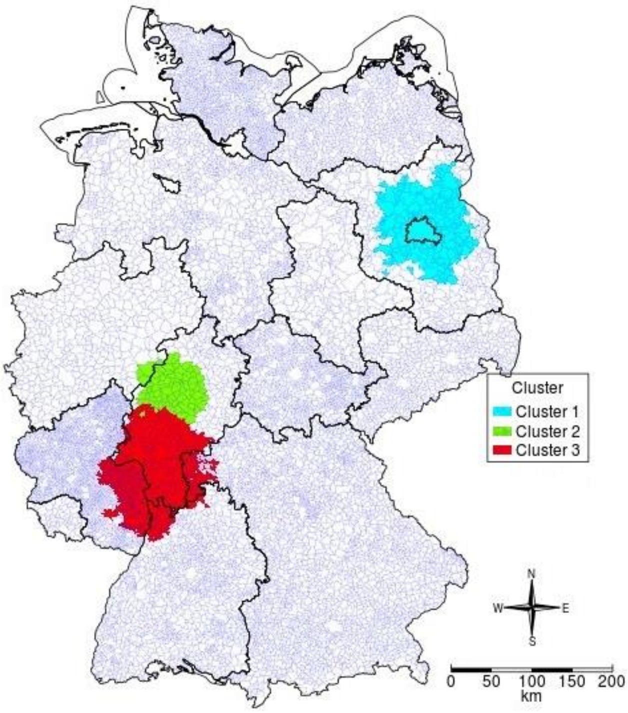

Figure 1: Exemplary illustration of the cluster index based on Brenner (2017) for the manufacture of basic pharmaceutical products (NACE code 211)

In addition, various control variables are included in order to account for other factors related to all three levels of analysis that might influence firm innovativeness in clusters. In line with several authors (e.g. Hervas-Oliver and Albors-Garrigos, 2009; McCann and Folta, 2011), firm age (years since foundation) and the company structure (dummy variable indicating whether firms are independent and do not belong to a corporate structure) are both included as firm control variables. Moreover, based on the spread of the internal R&D spending for the 50 different product categories, a proxy for firm's knowledge diversity is calculated which is assumed to positively influence firm innovativeness in clusters (Garcia-Vega, 2006; Miller, 2006). For the cluster level, it is additionally controlled for the cluster size, whose impact has been frequently discussed in the literature (Folta et al., 2006; McCann and Folta, 2011). In accordance with the most common approaches (McCann and Folta, 2008), cluster size is measured by the average number of employees between 2008 and 2015. Lastly, a dummy variable is included to control for research-intensive industries, which are assumed to be particularly inclined to create innovations, especially radical innovations (Tödtling et al., 2006).

To integrate the relation-specific data with the main firm-level database, it was necessary to match the company names, as a comparable identifier is missing. There are three main types of matching algorithms (Vectorial decomposition, Phonetic and Edit-distance) which all provide a similarity score between two strings by performing different string-based matching methods. As each matching algorithm has its advantages and disadvantages, four different matching algorithms[11] are applied in order to improve the overall matching quality (Raffo, 2017; Raffo and Lhuillery, 2009). In this context, the suggested name couples of all four matching algorithms were additionally checked manually by the author. The result of this detailed procedure is a unique firm-level database which combines several data sources from different levels of analysis. It contains information about 11,889 firms in Germany from which 1,391 firms are located within a cluster. As already highlighted before, most of the variables are averaged for the years 1997 to 2015 in order to reduce a possible measurement error bias created by year-to-year variability inherent in micro-level data (Rigby and Brown, 2015; Stern, 2010). By forming the average for each observation i over t = 1,…T, the following equation can be derived (Cameron and Trivedi, 2005):[12]

$$\bar{y}_i = \alpha + \beta\bar{x}_i + (\alpha_i - \alpha + \bar{\varepsilon}_i) \qquad (2.)$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$. The OLS regression of the across panels´ averages equals thereby the between estimator, being particularly useful to ascertain the effect of x when x changes between companies (Cameron and Trivedi, 2005; Gould, 2019). By taking the hierarchical nature of the data into account, an OLS regression with cluster correction of the standard errors is applied in the main analysis (table 3-4).[13] Such an empirical approach is more adequate than a standard OLS regression in which the corresponding standard errors are underestimated because of the nested data structure (McNeish, 2014; Moulton, 1990). It was additionally tested whether a multilevel regression would be more appropriate in this context. The corresponding results of the Likelihood-ratio test indicate however, that there is no significant improvement in comparison with an OLS regression with cluster correction. Thus, it is argued that the chosen methodical approach is valid to answer the underlying research question of this paper.

In general, the analysis can be divided into three parts. First, it is investigated whether firms located within a cluster are more innovative than firms outside clusters. Second, in line with Hervas-Oliver et al. (2018) as well as Hervas-Oliver and Albors-Garrigos (2009), the

[11] In more concrete terms, the Token, N-Gram, Soundex and Token Soundex algorithms were used.
[12] Due to some changes in the questionnaire of the Stifterverband, the dependent variable can only be averaged for the time period between 1997 and 2013. By only using the average, it is argued that the results will be unaffected. As a control and a further robustness check, the independent variables were also averaged for exactly the same time period as the dependent variable. The corresponding results of this robustness check are in line with the original results and can be provided upon request.
[13] The standard errors are clustered by regional cluster.

subsample of clustered companies is analysed separately to identify the conditions under which companies can gain from the cluster environment, specifically from knowledge spillovers. Third, for testing possible interaction effects and in accordance with Lee et al. (2001), the corresponding interaction terms are included one by one in order to avoid serious multicollinearity problems.

4. Results

Table 1 presents a pairwise correlation matrix for all independent variables.[14] In some cases the independent variables have relatively high correlations, raising a potential concern of multicollinearity. Therefore, in all models the corresponding Variance Inflation Factors are calculated. In no case did any of the Variance Inflation Factors come close or even exceed the standard critical value of 10 (Belsley, 1991; Myers, 1990; Stevens, 2002). Thus, multicollinearity is not a significant concern. Nevertheless, to prevent any kind of multicollinearity, and thereby increasing the stability of the model estimates of the coefficients even further, in some models certain independent variables are excluded.

Table 2 includes the results regarding the existence of a cluster effect on firm innovativeness by using an OLS regression with robust standard errors. The results of model 1 and model 2 indicate that being located in a cluster asserts a significant positive effect on firm innovativeness. Consistent with previous empirical results (e.g. Baptista and Swann, 1998; Bell, 2005), it can therefore be stated that due to localization economies firms within clusters are significantly more innovative than firms outside clusters.[15]

[14] The corresponding descriptive statistics for all main variables are presented in table 5 in the appendix.
[15] Following the remarks by McCann and Folta (2011), it is argued that the concern that the most innovative firms choose to locate in clusters, creating a potential selection bias, cannot be justified empirically nor theoretically. This can also be confirmed by the mean and the standard deviation of firm innovativeness within clusters, shown in table 5 in the appendix.

Table 1: Pairwise correlation matrix for the sample with cluster companies

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. Age	1.000															
2. Independence dummy	0.129*	1.000														
3. Innov. Capabilities	-0.265*	-0.037	1.000													
4. Number of linkages	0.101*	0.064*	-0.003	1.000												
5. No. Research institutes	-0.072*	0.034	0.110*	0.029	1.000											
6. Pace of tech. evolution	-0.038	-0.008	0.100*	0.044	-0.002	1.000										
7. Research-intensive industry	-0.076*	-0.028	0.094*	0.095*	-0.037	0.552*	1.000									
8. Central position in cluster	-0.004	-0.019	-0.056*	0.019	-0.118*	0.084*	0.007	1.000								
9. Knowledge similarity with cluster stock	0.182*	-0.004	-0.067*	0.053*	-0.018	-0.093*	-0.143*	0.072*	1.000							
10. Share basic research	-0.046	-0.015	0.032	-0.023	-0.000	-0.062*	-0.072*	-0.016	-0.020	1.000						
11. Share of cluster external relations	0.025	0.028	0.011	0.332*	0.084*	0.065*	0.047	0.015	0.044	-0.003	1.000					
12. Knowledge diversity	0.274*	0.070*	-0.173*	0.121*	-0.044	0.030	0.057*	0.079*	0.219*	-0.075*	0.105*	1.000				
13. Stock of alliances within cluster	-0.018	-0.015	0.104*	0.595*	0.040	0.156*	0.227*	0.032	0.004	-0.034	0.229*	0.050	1.000			
14. Stock of knowledge across cluster	-0.240*	0.006	0.622*	0.037	0.163*	0.136*	0.095*	-0.104*	-0.008	0.014	0.095*	-0.122*	0.185*	1.000		
15. Cluster size	0.066*	0.007	0.008	0.673*	0.020	-0.012	0.082*	0.012	0.003	-0.008	0.070*	0.049	0.693*	0.013	1.000	
16. Knowledge diversity within cluster	0.197*	0.027	-0.127*	0.072*	-0.083*	0.053*	0.103*	0.097*	-0.025	-0.023	0.056*	0.555*	0.090*	-0.221*	0.087*	1.000

Note: *p < 0.05

Table 2: OLS regression models with robust standard errors of single cross-section average over time for the full sample

Innovativeness (full sample)	*Model 1* *n = 11.530*	*Model 2* *n = 11.530*
Cluster dummy	0.642** (0.324)	0.639** (0.324)
Age	-0.003 (0.003)	-0.003 (0.003)
Independence dummy	-0.393 (0.442)	-0.417 (0.442)
Innovation Capabilities	1.907*** (0.410)	1.941*** (0.411)
Number of linkages	0.409*** (0.130)	0.412*** (0.131)
Number of research institutes	-0.016*** (0.004)	-0.015*** (0.004)
Pace of technology evolution	0.262*** (0.051)	0.262*** (0.051)
Firms knowledge diversity	1.159*** (0.036)	1.155*** (0.036)
Share of basic research	-0.044* (0.026)	
Share of experimental development		0.019 (0.012)
Constant	*0.687****	*-0.434*
R^2	*0.1244*	*0.1245*
*Robust Standard errors in parentheses. Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*		

Nevertheless, it is argued here that firms do not benefit equally and in the same manner from being located in a cluster. Consequently, table 3 tests the main formulated hypotheses regarding heterogeneous firm benefits within clusters. Model 3 illustrates the baseline model. As assumed, the coefficients for firm's knowledge diversity, industries research-intensity and cluster size remain consistently significant positive throughout the various models. In model 4 the variables for innovation capabilities, the degree of overlap between cluster and firm knowledge base, the firm´s cluster position, the participation and support of local research institutes as well as the share of basic research are added. Regarding innovation capabilities, contrary to the full sample, there is a relatively strong positive but insignificant effect on innovativeness, indicating that more innovation capabilities do not lead to a significant higher innovative performance. By considering the above median of innovation capabilities, model 5, however, reveals that there is a threshold effect of innovation capabilities. This means that a minimum level of innovation capabilities is necessary to benefit from the cluster environment. Additionally, the results of the squared coefficient, presented in table 3 (model 8), indicate that there is indeed a curvilinear (inverted 'U'-shaped) effect on firm innovativeness.

Table 3: OLS regression models with clustered standard errors of single cross-section average over time for the sample with cluster companies

Innovativeness (sample with cluster companies)	*Model 3* *n =1.343*	*Model 4* *n = 1.339*	*Model 5* *n = 1.340*	*Model 6* *n = 1.340*	*Model 7* *n = 1.340*	*Squared coefficients* *Model 8* *n = 1.340*	*Model 9* *n = 1.340*
Firm-level variables							
Innovation Capabilities		3.466 (2.146)				11.502** (5.238)	3.129 (2.110)
Innovation Capabilities above median			1.505** (0.620)	1.688*** (0.633)			
Innovation Capabilities squared						-11.302* (6.061)	
Number of linkages			0.504 (0.322)			0.521 (0.322)	0.521* (0.315)
Share of cluster external relations				0.269 (0.743)			
Knowledge similarity with cluster stock		1.644* (0.839)	1.511* (0.838)	1.620* (0.843)		1.415* (0.850)	9.932*** (2.550)
Knowledge similarity with cluster stock squared							-8.324*** (2.652)
Central position in cluster		1.039 (0.638)	0.971 (0.631)	0.994 (0.632)		1.012 (0.635)	1.138* (0.632)
Cluster and industry-level variables							
Share of basic research		0.185*** (0.069)	0.182*** (0.069)	0.181*** (0.068)	0.139* (0.078)	0.180** (0.071)	0.191*** (0.070)
Number of research institutes		-0.002 (0.016)	-0.002 (0.016)	-0.000 (0.016)	-0.003 (0.016)	-0.004 (0.015)	-0.002 (0.016)
Pace of technology evolution					0.170 (0.137)		
Stock of alliances within cluster					10.686*** (1.697)		
Stock of knowledge across cluster					-0.363 (3.186)		
Control variables							
Age	0.003 (0.007)	0.006 (0.007)	0.007 (0.007)	0.010 (0.008)	0.022*** (0.007)	0.008 (0.007)	0.006 (0.007)
Independence dummy	-2.193* (1.326)	-2.003 (1.301)	-2.453* (1.382)	-2.195* (1.296)	-1.312 (1.411)	-2.401* (1.377)	-2.265 (1.376)
Firms knowledge diversity	1.364*** (0.101)	1.359*** (0.105)	1.326*** (0.103)	1.354*** (0.103)		1.336*** (0.104)	1.270*** (0.104)
Research-intensive industry dummy	1.754*** (0.655)	1.966*** (0.676)	1.741*** (0.660)	1.924*** (0.675)		1.746*** (0.665)	1.644** (0.687)
Cluster size	0.001*** (0.000)	0.001*** (0.000)					
Knowledge diversity within cluster					1.438*** (0.185)		
Constant	*-0.181*	*-3.365****	*-3.398****	*-3.743****	*-2.128***	*-3.616****	*-3.994****
R^2	*0.1575*	*0.1683*	*0.1666*	*0.1582*	*0.0926*	*0.1671*	*0.1688*

Clustered standard errors in parentheses.
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

In order to analyse this pattern in more detail, figure 2 illustrates the corresponding quadratic prediction plot. Companies in clusters with a medium level of innovation capabilities (turning point equals a value of 0.509) present a higher effect on innovativeness than firms with very low or very high innovation capabilities. In the case of very high innovation capabilities, the effect on innovativeness can even turn into a negative one, which in accordance with Shaver and Flyer (2000) can be explained with unintentional knowledge spillovers to possible competitors. Overall, the presented results are in line with very recent findings by Hervas-Oliver et al. (2018) and confirm the asymmetric benefits referred to in hypothesis 1a.

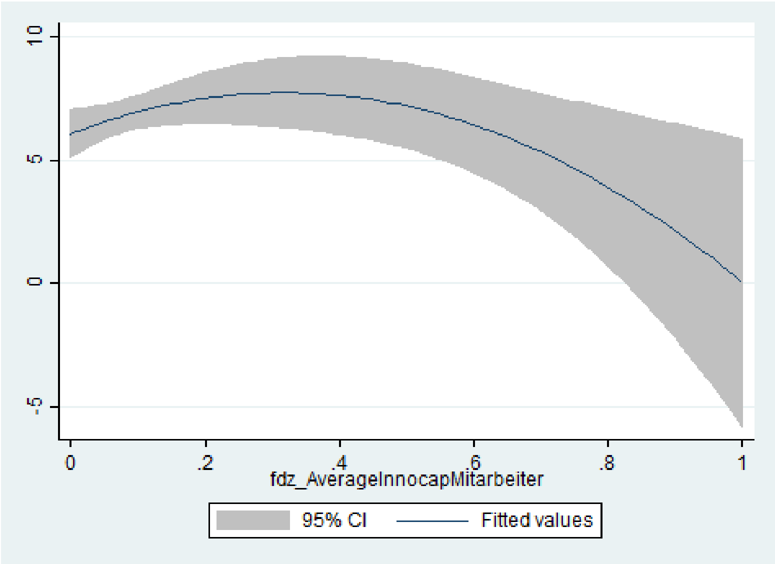

Figure 2: Two-way quadratic prediction plot between innovativeness and firm´s innovation capabilities

A similar pattern can be observed by analysing the more qualitative aspect of innovation capabilities, namely the degree of overlap between the firm´s and cluster´s knowledge stock. As indicated in table 3 (model 4) the effect of knowledge similarity with the cluster stock has a significant positive impact on firm innovativeness in clusters. The results of the corresponding squared coefficient, shown in table 3 (model 9), give again evidence for an inverted 'U'-shaped effect.

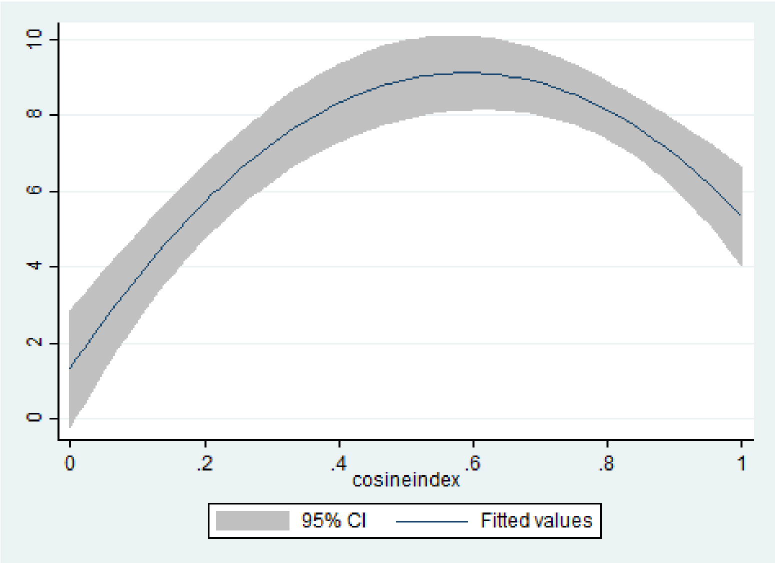

Figure 3: Two-way quadratic prediction plot between innovativeness and firm´s knowledge similarity with cluster stock

The non-linear relationship between the similarity of both knowledge stocks and firm innovativeness is depicted in figure 3. Especially companies in clusters with a moderate level of cognitive proximity (turning point equals a value of 0.597) profit the most. In accordance with Nooteboom (2000), it can be shown that too much proximity as well as too much distance decrease the effect on innovativeness. In the former case the predicted effect on innovativeness nearly turns to be zero. Consequently, it can be resumed that the mentioned results support the proposed assumption 1b.

In contrast to the previous two firm-level variables, the results in table 3 (model 4) reveal that the central position within clusters alone has a positive but insignificant impact on firm innovativeness. In other words, the location in the core of the cluster does not provide by itself a competitive advantage in terms of innovative performance. Therefore, the findings do not confirm the assumption 1d. This can eventually be explained with the different focus of the indicator for a firm´s central position in clusters. While other studies make use of network-specific indicators considering the concrete knowledge network within clusters (e.g. Giuliani, 2007), the cluster index applied here primarily stresses the geographical proximity between highly concentrated and specialized companies. The relations within clusters are instead considered separately in model 6.

Regarding the meso-level, it can be stated that the number of research institutes within clusters asserts a relatively small negative and insignificant effect on firm innovativeness in clusters. Hence, evidence suggests that instead of focusing primarily on the quantity of research institutes, it might be more appropriate to focus on the quality of these institutes and their collaborations with companies, as also suggested by other researchers (e.g. Agasisti et al., 2017; Barra et al., 2017; Tödtling et al., 2006).

By investigating the influence of the share of basic research on firm innovativeness in clusters, a significant positive effect is ascertained throughout all models (4-9). This means that a higher share of basic research leads to a significant higher innovative performance. This seems to be a cluster-specific effect, as in the full sample it flips to be (significantly) negative. Conducting basic research is therefore argued to be especially important for the innovative performance of companies in clusters. It provides protection against the competitive setting of clusters in which possible threats by competitors, in terms of new unexpected technological developments, may arise (Czarnitzki and Thorwarth, 2012; Grashof et al., 2019; Rosenberg, 1990). Hypothesis 3b can therefore be confirmed.

Model 5 tests the hypothesis 1b concerning the influence of the number of firm linkages on innovativeness. Contrary to the significant positive findings in the full sample, the results of the cluster sample show no significant effect of the number of linkages. In other words, in clusters the pure number of relationships, including cluster internal as well cluster external relationships, does not significantly foster firm innovativeness. Consequently, model 6 investigates the concrete impact of the share of cluster external relations further. The share of cluster external relations asserts a positive, however, statistically insignificant influence on firm innovative performance.[16] The effect of the share of cluster internal relations is respectively negative and insignificant.[17] To gain more insights about these relations, a possible interaction effect between the position within clusters and the cluster external relations is additionally analysed. The results, presented in table 4 (model 10), reveal that cluster external relations are especially important for firms located within the centre of clusters. In such a position, cluster external relations have a significant positive effect on firm innovativeness. A reasonable explanation for the difference between the centre and the periphery of a cluster can be found by comparing the cluster internal connectedness between both groups. Indeed, the mean of cluster internal relations is significantly higher in the centre than in the periphery of a cluster.[18] The risk for a lock-in situation, preventing innovations, is therefore potentially higher in the centre than in the periphery of a cluster. Thus, for companies located in the core of a cluster, it is particularly important to possess external relations. These cluster external relations provide a necessary channel for new knowledge that is different from the cluster internal knowledge. Regarding the relation-specific variables, it can therefore be resumed that the number of cluster external relationships does not significantly influence by itself firm innovative performance in clusters. Nevertheless, it becomes relevant when additionally considering the position within the cluster.

The seventh model of table 3 primarily focuses on the meso- and macro-level. The previous emphasized results for the share of basic research and the number of research institutes remain thereby unchanged. Additionally, the stock of knowledge of the cluster does not significantly influence firm innovative performance. So that the assumed generation of larger performance effects in clusters with a relatively high knowledge stock cannot be confirmed. Nevertheless, the findings of model 7 show at the same time that the stock of alliances within clusters asserts a relatively high significant positive impact on firm innovative performance. As expected, in an alliance-rich cluster the chance to extract knowledge from local and external connections seems to be enhanced, as it is much easier to come in contact with a broad variety of partners than in an alliance-poor cluster. Hypothesis 2b can therefore be supported.

Furthermore, the results of model 7 reveal that, in contrast to the full sample, the pace of

[16] As a further sensitivity test, the effect of the degree of cluster external relations instead of the share of cluster external relations is additionally investigated. The results remain thereby however the same (positive and insignificant) and can be provided upon request.
[17] To verify the results, model 6 has been replicated without the share of cluster external relations. Instead, a new dummy variable has been added, indicating whether firms own a moderate share of cluster internal (external) relations between 0.3 and 0.7. The corresponding results remain insignificant und can be provided upon request.
[18] Results can be provided upon request.

technology evolution becomes insignificant. While in general asserting a significant positive impact on firm innovativeness, in clusters the pace of technology evolution seems not to have a statistically relevant stand-alone effect. Hypothesis 3a can therefore not be supported. The results of both samples however indicate that the assumption of a negative effect should be reformulated into a positive one. This means that companies primarily active in rather young industries, normally characterized by a fast technology evolution (Clark, 1985; Klepper, 1997; Neffke et al., 2011), are, at least in the full sample, more innovative than companies engaged in mature industries.

However, by investigating potential interaction terms in table 4, it can be shown that the pace of technology evolution[19] asserts statistically relevant moderation effects. The results of model 11 reveal such an effect in the context of the firm´s innovation capabilities. In industries characterized by a fast pace of technology evolution, innovation capabilities have a positive significant impact on firm innovative performance. For companies active in such industries it is therefore especially important to own sufficiently high innovation capabilities, because they allow to access and integrate new knowledge, which is frequently changing under a rapid technology evolution.

A possible interaction effect between the pace of technology evolution and firm knowledge similarity with the cluster stock is additionally tested. Under a rapid technology evolution, it is assumed that firms need to have a larger cognitive distance towards the cluster knowledge stock in order to be more open to new external ideas, thereby preventing a possible lock-in situation. The corresponding interaction term indeed asserts a negative, however, insignificant impact on firm innovativeness.

Finally in model 13, it is investigated whether a fast pace of technology evolution moderates the relationship between firm cluster external relations and firm innovativeness. As assumed, under a fast pace of technology evolution, firm cluster external relations assert a strong significant effect on firm innovative performance. This means that these cluster external relations are especially crucial in industries characterized by a fast pace of technology evolution. The rapid evolution requires that firms gain access towards external knowledge sources in order to secure that their current knowledge stock does not become obsolete in the near future.

Table 4: OLS regression models with clustered standard errors of single cross-section average over time for interaction effects (sample with cluster companies)

[19] Here calculated as a dummy variable, where 1 means that the pace of technology evolution is equal or higher than the corresponding 75th quantile. The 75th quantile has been chosen, as at the very end of the distribution (from the 90th quantile upwards) the number of observations for a fast technology evolution becomes too small for a further analysis. Nevertheless, in light of other contributions using for example simply the mean as a threshold (e.g. Audretsch and Feldman, 1996), it is argued that the 75th quantile represents a reasonable threshold for industries with a fast pace of technology evolution.

Innovativeness (sample with cluster companies)	*Model 10 n = 1.340*	*Model 11 n = 1.340*	*Model 12 n = 1.340*	*Model 13 n = 1.340*
Firm-level variables				
Innovation Capabilities		2.173 (2.214)		
Innovation Capabilities above median	1.580** (0.628)			
Cluster external relations	-0.177 (0.225)			0.472 (0.345)
Knowledge similarity with cluster stock			1.682** (0.818)	
Central position in cluster	0.527 (0.634)			
Periphery position in cluster				
Cluster and industry-level variables				
Share of basic research	0.174** (0.071)	0.176** (0.069)	0.180*** (0.067)	0.175** (0.070)
Number of research institutes	-0.005 (0.016)	-0.009 (0.017)	-0.004 (0.017)	-0.006 (0.017)
Fast technology evolution dummy		0.049 (1.293)	3.214* (1.867)	0.742 (1.032)
Interaction terms				
Cluster external relations x Centre	1.125*** (0.264)			
Fast technology evolution dummy x Innovation Capabilities		12.583** (5.675)		
Fast technology evolution dummy x Knowledge similarity with cluster stock			-1.802 (3.027)	
Fast technology evolution dummy x Cluster external relations				2.990*** (0.748)
Control variables				
Age	0.009 (0.007)	0.008 (0.007)	0.003 (0.008)	0.003 (0.007)
Independence dummy	-2.175* (1.233)	-2.282* (1.239)	-2.147* (1.280)	-2.913** (1.332)
Firms knowledge diversity	1.366*** (0.100)	1.429*** (0.103)	1.383*** (0.105)	1.327*** (0.104)
Research-intensive industry dummy	1.579** (0.652)			
Constant	*-2.427****	*-1.2658***	*-1.641***	*-0.527*
R^2	*0.1754*	*0.1519*	*0.1480*	*0.1693*
*Clustered standard errors in parentheses. Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*				

Overall, evidence is found that several variables from different levels of analysis directly as well as interactively influence firm innovative performance in clusters. The derived results are, on the one hand, in line with the literature reporting a significant positive relationship between being located in a cluster and firm innovativeness (e.g. Baptista and Swann, 1998; Bell, 2005). On the other hand, the results also suggest that firms benefit unequally within the cluster environment. The results, however, differ in this context from similar studies (e.g. Hervas-Oliver et al., 2018; McCann and Folta, 2011), because variables from three different levels of analysis are seperately as well as interactively tested, thereby enriching the current discussion about contextual conditions that contribute to firms' heterogenous benefits within clusters. As a further robustness check of the presented results, all models have been calculated for an alternative dependent variable: radical innovativeness. In contrast to the main dependent variable, radical innovativeness is calculated only by the average share of the firm´s product innovations in previous three years sales (1997-2013), which are new to the market and/or new to the firm.[20] The corresponding results are in line with the findings for firm innovativeness. The relation-specific variables as well as the pace of technology evolution have been additionally tested for different time periods. In both cases no relevant changes could be detected.[21]

5. Discussion and conclusion

Regional clusters have become an inseparable component of modern economies. However, it is still rather unclear whether companies' innovative performance really benefits from being located in a cluster and, even more importantly, which conditions are necessary to profit particularly from the cluster environment (Festing et al., 2012; Frenken et al., 2013; Martin and Sunley, 2003). By integrating theoretical perspectives from the strategic management (e.g. RBV, RV and MBV) as well as economic geography literature (e.g. cluster approach), these essential questions are answered with a specific focus on the Marshallian externality of knowledge spillovers. The corresponding main empirical results for the three different levels of analysis (micro-level, meso-level, and macro-level) can be resumed as follows: (1.) Being located in a cluster increases on average firm innovative performance. (2.) However, firms gain unequally from the cluster environment. To profit the most from available knowledge spillovers firms need to have, for example, a medium level of innovation capabilities and knowledge similarity with the cluster stock. Besides, a high share of basic research and a pronounced stock of alliances within clusters are also beneficial conditions for firm innovativeness in clusters. Consequently, in light of the results for the stock of alliances within clusters, it can be argued that the concept of local buzz and global pipelines, proposed by Bathelt et al. (2004), can be extended with a cluster dimension. (3.) Nevertheless, evidence for interaction effects between the three levels of analysis can be found. Due to the significant higher number of cluster internal relations in the cluster centre, promoting a lock-in situation, it is crucial that firms located within the centre of a cluster possess sufficient cluster external relationships. Apart from the concrete location within clusters, the pace of technology evolution also has to be considered as a moderating variable. Under a rapid technology evolution, firms need to own sufficiently high innovation capabilities to gain from knowledge spillovers. They allow for access to and

[20] In light of the literature dealing with radical innovations (Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010), the author is aware of the fact that the applied indicator here is only a rough proxy for radical innovations, although it still considers the novelty of an innovation more explicitly than other frequently used innovation-related indicators, such as patent dummies (e.g. McCann and Folta, 2011).
[21] The results of all robustness checks can be provided upon request.

integration of new knowledge, which is frequently changing in an industry with rapid technology evolution. Moreover, this paper provides evidence is provided that the rapid evolution also requires that firms have cluster external relations through which they can access external knowledge sources in order to guarantee that the current knowledge stock does not become obsolete.

However, there are some limitations to this study which can be seen as starting points for future research. First of all, the study does not consider the dynamic evolution across the cluster life cycle (e.g. Menzel and Fornahl, 2010). Due to data availability, the corresponding cluster index could only be calculated for the year 2012. Future research may investigate several years to capture the cluster life cycle and its possible impact on the sustainability of firm innovative performance in clusters. In this context, panel-regressions are also an appropriate suggestion. The underlying data constraints of this study[22] have prevented applying such approaches. Instead the study employed an OLS regression with clustered standard errors to a single cross-section of variables average over time (between estimator). Historically, such an approach has, however, been criticized due to a concern that omitted variables, represented by the individual effects of the error term, may be correlated with the independent variables, leading to inconsistent results. Nevertheless, such a potential bias is also valid for other approaches.[23] Moreover, it only constitutes one of several possible misspecifications of such models (Baltagi, 2005; Hauk Jr. and Wacziarg, 2009; Mairesse and Sassenou, 1991; Stern, 2010). In view of the underlying research question concentrating more on the between-variation and the available data, it is therefore stated that the selected methodical approach is suitable despite its limitations in contrast to panel-regressions (Griliches and Mairesse, 1984; Hauk Jr. and Wacziarg, 2009; Kafouros, 2008). It is indeed quite common to exploit cross-sectional data in empirical studies using innovation surveys (Mairesse and Mohnen, 2010). So it may be a promising research gap for future studies to implement panel-regressions in order to investigate properly the dynamic evolution across the cluster life cycle. Furthermore, the concrete partners and their knowledge profiles are not taken into consideration in the applied relation-specific variables. For future research it may be interesting to analyse in detail whether and under which conditions the type of partners (universities, small and medium-sized enterprises etc.) and their knowledge profiles matter for firm innovativeness in clusters. Lastly, the analysis here is limited to the empirical setting within Germany. Future studies may broaden this research setting by considering countries from different economic development levels. Consequently, possible country effects could be investigated.

[22] Since the underlying survey questions of the dependent and independent variables are only inconsistently answered over the years (e.g. Mairesse and Mohnen, 2010), a regression on a balanced panel database would result in a significant loss of observations, thereby creating a potential bias. In more concrete terms, in the underlying panel sample of this study, 50% of the firms answer only four times (between 1997 and 2015) the corresponding survey questions.

[23] The results of the omitted variables tests carried out here, however, suggest that such a bias is not a major concern in this study.

Nevertheless, all in all it can be resumed that the derived results about the conditions necessary to profit from knowledge spillovers contribute to closing a still ubiquitous research gap. Additionally, the results also have a pragmatic meaning for companies as well as policy makers, because both can evaluate better under which conditions firms' innovative performance is more likely to benefit from locating within clusters. Instead of realizing generic agglomeration and cluster policies, policy makers should establish initiatives that are customized to the specific firm, cluster and market/industry characteristics. Such a context-oriented cluster policy approach would efficiently support those firms that really need help to benefit from the cluster and thereby work towards creating a cluster environment from which all companies can gain.

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Appendix

Table 5: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Innovativeness	1391	6.642	11.991	0	80
Age	1344	44.763	41.477	0	355
Independence dummy	1391	0.040	0.195	0	1
Innov. Capabilities	1391	0.124	0.166	0	1
Number of linkages	1391	0.447	2.225	0	55.900
No. Research institutes	1391	4.702	15.213	0	85
Pace of tech. evolution	1391	1.708	2.638	0	18.399
Research-intensive industry	1391	0.451	0.498	0	1
Central position in cluster	1391	0.500	0.500	0	1
Knowledge similarity with cluster stock	1391	0.592	0.332	0	1
Share basic research	1387	5.845	5.038	0	67.828
Share of cluster external relations	1391	0.264	0.438	0	1
Knowledge diversity	1391	4.300	3.177	0	17
Stock of alliances within cluster	1391	0.064	0.186	0	4.658
Stock of knowledge across cluster	1391	0.114	0.103	0	1
Clustersize	1390	164.006	1177.277	1.385	41667.94
Knowledge diversity within cluster	1391	4.300	1.763	0	12