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Sinking or swimming in the cluster labour pool? – A firm-specific analysis of the effect of specialized labour

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Abstract

Human resources are a key factor for firm success, particularly nowadays when most industrial economies face an increasing shortage of qualified labour. With their pooled labour markets, regional clusters have been shown to be a preferable location for firms in order to satisfy their demand for skilled employees. Nevertheless, in light of possible disadvantages (e.g. labour poaching) and the broad field of studies dealing with firm performance differentials, the prevalent assumption that all companies profit equally from the specialized labour pool in clusters must be questioned. Consequently, the aim of this paper is to empirically investigate the conditions and mechanisms through which companies located in clusters can gain, in terms of innovativeness, from the specialized labour pool. By synthesizing theoretical streams 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 examined separately as well as interactively. Apart from revealing that being located in a cluster indeed increases on average firm innovativeness, one of the central findings is that firms benefit unequally within the cluster environment depending on the specific firm-level, cluster-level, industry-/market-level conditions and their respective interactions.

Keywords: specialized labour pool, cluster, agglomeration, firm performance differentials, innovation

JEL Codes: C31, J24, L22, O30, R10, R23

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1. Introduction

Human resources are commonly seen as a key factor for firm success (Barney and Wright, 1998; Pfeffer, 1994; Stiles and Kulvisaechana, 2003). They offer the potential to advance firms' efficiency, to exploit novel business opportunities and to prevent approaching competitive threats (Barney, 1991; Klumbies, 2015; Lepak and Snell, 2002). In light of an adverse demographic development in most industrial economies exacerbating the currently increasing shortage of qualified labour, particularly nowadays human resources have become even more important for profitable and sustainable firm performance. In Germany for example 31.4% of the establishments reported problems in finding sufficient applicants (Bossler et al., 2017; IAB, 2017; Martinez-Fernandez and Weyman, 2012). To satisfy their demand for skilled employees, it has been theoretically as well as empirically shown that companies tend to locate in agglomerations or clusters[1] providing a pooled labour market (Combes and Duranton, 2006; Ellison et al., 2010; Overman and Puga, 2010). The economist Alfred Marshall asserted, already in the year 1920, that "(…) a localized industry gains a great advantage from the fact that it offers a constant market for skill." (Marshall, 1920, p. 271). Subsequent scientific contributions additionally highlighted in this context that clusters create a common market pool for workers with specialized skills that offers advantages in terms of risk reduction and efficiency gains in the job search process for both the workers as well as the hiring firms (David and Rosenbloom, 1990; Krugman, 1991).

So far, most of the studies dealing with the externality of labour pooling and firm performance, however, do not consider the specific context. Instead, 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). Nevertheless, there is indeed also evidence for possible disadvantages from the clustered labour pool referring to high competition between companies for new employees and labour poaching which is part of this high competition (Combes and Duranton, 2006; Otto and Fornahl, 2010). In view of these potential negative effects and the broad field of studies dealing with firm performance differentials (Dyer and Singh, 1998; Van Oort et al., 2012; Vega-Jurado et al., 2008) it becomes obvious that the idea of equal gains for all companies located in a cluster is rather questionable.

Frenken et al. (2013) therefore make a call to investigate the conditions and mechanisms through which the firm-specific advantages of localization economies can be realized. The analysis should thereby sepeartely consider the three main components of localization

[1] 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.

economies, referring to specialized labour markets, specialized inputs and knowledge spillovers. Consequently, the aim of this paper is to respond to this call for the Marshallian component of specialized labour by answering the following research question: Under which conditions can a company located in a cluster profit from the specialized labour pool?

The theoretical conceptualization of potential contextual variables is thereby based on an integration of the theoretical perspectives from the strategic management (e.g. resource-based view, relational view and market-based view) and the economic geography literature (e.g. cluster approach). As a result and in contrast to recent studies examining the firm performance heterogeneity within clusters only for one level of analysis, in this paper three different levels of analysis (micro-level, meso-level and macro-level) are therefore separately as well as interactively investigated by applying a OLS regression with clustered standard errors of single cross-section average over time, equalling the between estimator. Hence, for the empirical analysis, varying data sources are integrated, ranging from firm-level to market and industry-level data. The corresponding unique multilevel dataset consists of 11,500 companies in Germany. The selected methodical approach is in this context appropriate because it considers the hierarchical data structure, the context dependency and the year-to-year variability inherent to micro-level data (McNeish, 2014; Moulton, 1990; Rigby and Brown, 2015).

By examining the separate as well as interactive influence of variables from three different levels of analysis, the paper enriches the current discussion about firm performance differentials within clusters (e.g. Hervas-Oliver et al., 2018), because it offers a more systematic and comprehensive analysis of the contextual conditions shaping firm performance within clusters. Besides contributing to closing a still ubiquitous research gap, the paper also offers a rather pragmatic value, especially in times of an increasing shortage in skilled labour, because companies as well as policy makers can evaluate better under which conditions the potential advantages of the specialized labour pool in clusters are more likely to be realized.

The remainder of this paper is organized as follows: The second section presents the theoretical background, highlighting the current debate about specialized labour and elaborating the corresponding hypotheses for each level of analysis.[2] In the third section, the applied methodical approach, the multilevel sources of the data and the corresponding variables are discussed in detail. The empirical results are thereafter presented in the fourth section. The paper will end with some concluding remarks, including limitations to this study

[2] The first group of hypotheses therefore covers the micro-level, while the second refers to the meso-level and the third group of hypotheses deals with the macro-level.

as well as promising areas for future research.

2. Theoretical background of the labour pool in clusters and firm performance

Despite the popularity and widespread application of the cluster term in various disciplines, there still remains definitional and conceptual dissension about clusters, resulting in a loss of explanatory power (Brown et al., 2007; Malmberg and Maskell, 2002; Martin and Sunley, 2003; Šarić, 2012). Having a clear understanding about the main definitional elements is therefore the first step to analyse adequately the firm-specific cluster effect. Instead of theoretically elaborating a new (conceptual) cluster definition, this study exploits, however, the following working definition, derived through a comparative empirical approach in Grashof (2017): "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, 2017, p. 4f.).

Marshall (1920) made one of the pioneering contributions that consider the benefits that firms can gain from being located in close proximity to similar firms. He emphasized 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).[3]

The paper will specifically focus on the access to specialized labour. It has been emphasized that clusters create a common market pool for specialized workers that provides benefits for both the employers as well as the employees (Krugman, 1991; Marshall, 1920). The reduction of risk is one of these two-sided benefits. For employees, the spatial concentration of similar thematic firms reduces the risk of becoming unemployed, as they are able to attain work from multiple employers. At the same time, employers can minimize their risk of not finding and hiring the right job candidates (David and Rosenbloom, 1990; Krugman, 1991). Furthermore, the pooling of specialized employers and employees in close geographical distance facilitates the search and screening process for both sides. In absence of such a pooled specialized labour market, companies and workers alike have to search on the national or even international labour market, resulting in relatively high search costs and in potentially lower matching qualities (Amend and Herbst, 2008; Otto and Fornahl, 2010). With their pooled labour markets, clusters therefore help to alleviate the typical hold-up problem. Specialized workers are more willing to make industry-specific investments in their human

[3] 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.

capital when they believe that they can appropriate the corresponding benefits, which is particularly the case in a highly competitive setting such as a cluster (Almazan et al., 2007; Amend and Herbst, 2008; Rotemberg and Saloner, 2000).

Despite these advantages, there also exist possible disadvantages of being located in a pooled specialized labour market. Companies located in clusters are confronted with fierce competition in the recruitment of new talented employees. One extreme form of this competition refers to labour poaching, meaning that current employees are hired by competing firms. The associated costs of this poaching are twofold. First, due to the efficient matching process resulting in an alleviated mobility of employees, competitors can have access to the firm´s own knowledge embodied in its employees by recruiting them. In this way, competing firms can increase their relative competitive advantage over other firms. Second, to avoid such a loss of knowledge, companies may be more inclined to pay higher wages. Thereby, they can indeed retain their current human capital, but this comes at the cost of higher personnel expenses. In general, it can therefore be resumed that companies can realize advantages as well as disadvantages from the pooled labour market in clusters (Combes and Duranton, 2006; Otto and Fornahl, 2010).

While the reviewed theory about the specialized labour pool within clusters and its potential (dis-)advantages is relatively well elaborated, the literature is, however, nearly silent about the concrete conditions and mechanisms through which those outcomes can be realized (Frenken et al., 2013; McCann and Folta, 2011). In light of the resource-based view (RBV), this silence is particularly surprising. The resource-based view of the firm is one of the most widely accepted theoretical perspectives in the field of strategic management (Newbert, 2007; Steffen, 2012), but it has also been applied in the cluster context (Hervas-Oliver and Albors-Garrigos, 2007; Hervas-Oliver and Albors-Garrigos, 2009). Originally emerged from the contributions of Penrose (1959), Rubin (1973) and Wernerfelt (1984), the RBV has since then continuously been advanced, highlighting for example the importance of dynamic capabilities to actually utilize the available resource bundles (Teece et al., 1997) as well as focussing on specific resources such as knowledge (Grant, 1996).[4] The core idea of the RBV deals with the firm´s internal resource base and how firms can make use of these resources in order to gain a competitive advantage. It is further assumed that resources are immobile and unequally distributed between companies. Both assumptions are necessary for the existence of different resource endowments and its persistency over time. The strength of firms' resources is given by their characteristics, namely whether they are valuable, rare, non-substitutable and imitable (Barney, 1991; Newbert, 2007; Steffen, 2012). In line with

[4] For a good overview see for example Newbert (2007).

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).[5]

In the literature firms' human resources and their corresponding human capital have been regarded as central determinants for firm competitive advantage and have therefore been frequently analysed (De Saá-Pérez and García-Falcón, 2002; Newbert, 2007). Even though some evidence is found for a positive effect, also on firm innovative performance (e.g. Bornay-Barrachina et al., 2017; Cabello-Medina et al., 2011), the results are in general not as consistent as one would assume (Newbert, 2007). One plausible explanation here for refers to the missing consideration of associated variables with human capital (Bornay-Barrachina et al., 2017; Newbert, 2007). Building on the RBV and its supplement theoretical perspective of dynamic capabilities, it has been highlighted in this context that companies need to own the necessary human resource capabilities to realize a competitive advantage (Hatch and Dyer, 2004; Newbert, 2007; Snell et al., 1996). Companies that are able to identify, acquire and train the most adequate talents are argued to own a significant competitive advantage (De Saá-Pérez and García-Falcón, 2002; Hatch and Dyer, 2004). While the role of human resource capabilities for firm performance has been in general theoretically as well as empirically investigated, it has not been examined yet in the cluster environment. Nevertheless, in view of the previous theoretical and empirical contributions, it can be assumed that human resource capabilities are essential for firms to gain from the specialized labour pool in clusters. It is indeed plausible that firms lacking sufficient human resource capabilities are not able to profit so much from the specialized labour pool within clusters, because they are not capable of finding the most adequate candidates and, even more important in a competitive environment such as a cluster, they cannot hire and/or hold the best fitting labour forces. Thus, the following hypothesis is proposed:

Hypothesis 1a: The human resource capabilities of a firm have a positive effect on firm innovative performance in clusters.

Moreover, the ongoing changes in the labour market (e.g. demographic change and migration), which are sometimes also politically fostered, such as in the case of women´s increased labour participation, result in a more heterogeneous workers' landscape. Besides the mentioned human resource capabilities, firms therefore have also to consider the diversity of their human resources (Garnero et al., 2014; Parrotta et al., 2014). The diversity

[5] Although a clear definition of resources has not been developed yet, the definition by Barney (1991) has become a standard definition that has been commonly used (Hervas-Oliver et al., 2014; Steffen, 2012).

of human resources offers, however, advantages as well as disadvantages. On the one hand, diversity in terms of culture, age and gender can provide diverse ideas, problem-solving abilities and new attitudes, which in turn stimulate innovations. But on the other hand, increasing employee diversity may lead to communication problems or personal conflicts. The associated costs can potentially offset the gains from a diverse stock of employees (Østergaard et al., 2011; Parrotta et al., 2014; Schneider and Eckl, 2016). Consequently, it has been highlighted by some authors that the specific context must be taken into consideration when analysing the potential impact of employee diversity on firm performance (Dwyer et al., 2003; Garnero et al., 2014).

As mentioned briefly above, one of the main aspects of diversity, also from a policy perspective, refers to gender equality (Kladroba and Eckl, 2019). While the relationship between gender diversity and firm innovativeness has recently gained some attention (Horbach and Jacob, 2017; Østergaard et al., 2011; Schneider and Eckl, 2016), the specific environment of clusters remains yet to be properly examined. In light of the importance of (informal) linkages for accessing the available knowledge within clusters highlighted in the cluster approach (e.g. Balland et al., 2016; Ferriani and MacMillan, 2017) and the gender-segregated socialization patterns (e.g. Gray and James, 2007; Ruiz-Jiménez et al., 2016), it can however be argued that gender diversity provides access to a broader knowledge network, thereby promoting potential benefits from knowledge spillovers. Moreover, since gender diversity is ultimately associated with a more heterogeneous firm knowledge base, it is likely that such firms are more open to new ideas and develop higher absorptive capacities (e.g. Østergaard et al., 2011), which have been shown to influence firm innovative performance within clusters (Grashof, 2018; Hervas-Oliver et al., 2018). Thus, the following hypothesis is proposed:

Hypothesis 1b: The gender diversity of the firm´s human resource stock has a positive effect on firm innovative performance in clusters.

As already indicated in the previous theoretical discussion, the specialized labour pool within clusters makes the search and screening process for employers as well as employees more efficient. Nevertheless, in the literature it is also suggested that this is particularly the case when the corresponding skills of the employees located in a cluster are similar to the underlying core activities of the clustered firms (Amend and Herbst, 2008; Otto and Fornahl, 2010). Building on these theoretical insights, it can be further assumed that it is beneficial for firms to own a human resource stock with similar skills compared to the overall cluster. It is supposed that such a high degree of overlap minimizes the potential of mismatches, thereby

contributing in the end to firm innovativeness. Thus, the following hypothesis is proposed:

Hypothesis 1c: The degree of overlap between the overall labour qualifications within the cluster and the labour qualifications of the firm has a positive effect on firm innovative performance in clusters.

The labour market pooling within clusters additionally encourages intensive employee mobility. Since knowledge is embedded in people, such a pronounced mobility of specialized workers is argued to be a crucial mechanism for knowledge diffusion among firms, providing new ideas as well as competences and thereby fostering firm innovative performance (Boschma et al., 2009; Erikson and Lindgren, 2009; Otto and Fornahl, 2010). For example, in their large empirical analysis of almost 257,000 workplaces in Sweden, Erikson and Lindgren (2009) found that localized labour market-induced externalities via job mobility significantly influence firm performance (Erikson and Lindgren, 2009). Labour mobility is especially important in this context for the dissemination of tacit knowledge, such as experiences and routines that cannot be easily codified in the form of texts or documents (Almeida and Kogut, 1999; Bienkowska et al., 2011; Erikson and Lindgren, 2009; Power and Lundmark, 2004). Moreover, new employees can likewise expand the overall network by bringing along previously established business and personal contacts (Bienkowska et al., 2011; Zellner and Fornahl, 2002). Besides these advantages, the mobility of labour is also argued to be associated with potential costs such as labour poaching that results in a knowledge drain (Combes and Duranton, 2006; Otto and Fornahl, 2010). The same reasoning can also be expected for the temporary exchange of human resources in the form of out-going expatriates and in-going inpatriates, which are quite prevalent measures in contemporary human resource management (Fang et al., 2010; Harzing et al., 2016; Reiche, 2006). However, despite its popularity, the concrete influence of the corresponding human capital exchange intensity still remains rather unclear in the competitive environment of clusters. Nevertheless, in line with the extension of the RBV, the relational view (RV), concentrating on relational resources that go beyond firm boundaries (Dyer and Singh, 1998; Lavie, 2006), and the cluster approach, stressing the importance of labour mobility, it is assumed that the exchange of human capital is an essential channel for inter-firm knowledge transfers, and in the end, for firm innovative performance. Thus, the following hypothesis is proposed:

Hypothesis 1d: The human capital exchange intensity has a positive effect on firm innovative performance in clusters.

For the recruitment of the best talents it is additionally essential for companies to be visible for potential applicants. Particularly in a highly competitive setting of similar firms, such as in clusters, it is plausible that the visibility, acting as a differentiation signal, plays a crucial role in attracting the most talented workers from the specialized labour pool (Cable and Turban, 2003; Molina-Morales and Martínez-Fernández, 2004; Williamson et al., 2010). The network literature highlights that apart from information benefits (Bell, 2005; Zaheer and Bell, 2005), firms located in the centre can also profit from a higher visibility and from status gains (Ferriani and MacMillan, 2017). Consequently, it can be assumed that the firm´s centrality within the corresponding cluster may determine to some extent the potential of gaining from the specialized labour pool within clusters. 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.

Contrary to most studies dealing with clusters and firm performance[6], it is postulated here that apart from firm-specific conditions, it also necessary to consider the specific cluster attributes, which can likewise be quite heterogeneous (McCann and Folta, 2008). One important attribute in this context refers to the stock of human resources of the cluster. With an increase of specialized workers in the pooled labour market in clusters, it is likely that the matching as well as search processes of the corresponding firms become even more efficient due to the higher supply of specialized labour (Folta et al., 2006; McCann and Folta, 2008). Nevertheless, evidence for potential congestion costs (e.g. fierce competition) has also been found (Folta et al., 2006; Zucker et al., 1998). In line with the principal rationale of the economies of agglomeration (e.g. Arthur, 1990), it is however assumed that the stock of human resources of the cluster asserts a positive impact on firm innovative performance. Thus, the following hypothesis is proposed:

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

Apart from the quantity of the pooled labour market in clusters, the corresponding quality should be considered additionally. On the firm-level, it has already been shown that the quality of the human resources, measured for example by the educational degrees, constitutes a significant determinant of firm innovativeness (Cabello-Medina et al., 2011; Huiban and Bouhsina, 1998; Vinding, 2006). Regarding clusters, however, it has been implicitly assumed that the quality of the labour pool is homogenously distributed among all

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

clusters and that therefore the access to it is one of the main advantages of being located in clusters (e.g. Oakey and Cooper, 1989). In line with the theoretical elaborations by McCann and Folta (2008), this work assumes that clusters vary in the quality of their respective labour pools. Consequently, firms located in clusters with a relatively high quality of the labour pool are presumed to provide a more beneficial environment for innovations than clusters with a rather low quality of the labour pool. Thus, the following hypothesis is proposed:

Hypothesis 2b: The quality of the labour pool within the cluster has a positive effect on firm innovative performance in clusters.

Furthermore, the gender diversity within clusters is related to the quality of the pooled labour market. Even though gender diversity has primarily been investigated on the micro-level (Dwyer et al., 2003; Täube, 2005), it can be argued that specialized labour pools within clusters characterized by a high gender diversity can potentially offer a high quality of human capital, as the localized pool of different experiences and ideas becomes broader (Horbach and Jacob, 2017; Schneider and Eckl, 2016). As a result, the innovativeness of the corresponding firms is expected to be fostered. Thus, the following hypothesis is proposed:

Hypothesis 2c: The gender diversity of the labour pool within the cluster has a positive effect on firm innovative performance in clusters.

Similar to the quality of the labour pool, it has also been implicitly assumed that the matching process is equally efficient in all clusters. It has indeed been verified that the specialized labour pool within clusters makes the matching process between employers and employees more efficient (Amend and Herbst, 2008; Otto and Fornahl, 2010). Nevertheless, in light of its structural differences, it is reasonable to assume that the labour pools within clusters may vary in their matching capacities. Thus, the following hypothesis is proposed:

Hypothesis 2d: The matching capacities of the labour pool within the cluster have a positive effect on firm innovative performance in clusters.

However, in accordance with the market-based view (MBV), it is claimed that apart from the firm-specific and the cluster-specific conditions, it is additionally crucial to consider the concrete market and industry environment, whose impact on firm performance has been widely acknowledged (Kohlbacher et al., 2013). The core idea of the MBV is that firm success is primarily determined by the external environment, such as the specific market conditions (Porter, 1980; Steffen, 2012). Building on this prominent theoretical stream and on

the two scientific papers of Suarez and Lanzolla (2005 and 2007), it is assumed that the pace of technology evolution influences firm innovative performance in clusters. The pace of technology evolution is typically captured through a technology S-curve, depicting the technological improvements over time 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 technology evolution, it is likely that the knowledge and competencies embodied in the human resources become rather unsuitable or even obsolete. The corresponding advantage from the access to specialized labour within clusters is therefore assumed to diminish under these circumstances (Filippetti and Guy, 2016; Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Incumbent employees may additionally have strong incentives to prevent any mayor shifts in companies' strategic direction due to their own personal career interests which are at risk if the required competence profile dramatically changes. Such a behaviour can of course result in a lock-in situation, thereby hampering firm innovative performance (Sørensen and Stuart, 2000). Thus, the following hypothesis is proposed:

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

Moreover, the pace of market evolution, varying as much as the pace of technology evolution, is also assumed to influence firm innovativeness in clusters. In a fast-growing market, measured for example in sales or household penetration, it becomes more attractive for employees to specialize themselves in the corresponding industry. Consequently, the supply of specialized labour in the particular industry increases, leading to a decreased advantage derived from the previously rather unique access to specialized labour in clusters, as the supply increases in total, also outside of clusters (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Regarding the employers, it can be further argued that a fast-growing market not only attracts more labour, but also more competitors, potentially even from indirectly related industries. The resulting fierce competition may then come at the cost of innovative new ideas (Kohlbacher et al., 2013). Thus, the following hypothesis is proposed:

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

Lastly, the market risk is additionally suggested to have a significant impact on firm innovativeness in clusters. Under a high market risk, implying high uncertainty, it is likely that human resource decisions, frequently entailing large sunk costs (e.g. search and training

costs) which are often partially irreversible (e.g. long-term labour contracts), are postponed in order to avoid costly mistakes (Ernst and Viegelahn, 2014; Schaal, 2017). Due to the held-back investments in the search and the hiring of new employees, companies will consequently not profit from the specialized labour pool within clusters. The similar reasoning can also be applied to the human capital-related investment decision of the employees. The investment in industry-specific skills is a rather major and long-term oriented decision, since the corresponding knowledge is limited in its applicability. Hence, in a risky market environment, employees may also postpone their industry-specific investment decisions in order to prevent mistakes in their career advancements (Filippetti and Guy, 2016). As a consequence of this wait-and-see behaviour, the overall quality of the specialized labour pool within clusters may in turn be negatively affected. Thus, the following hypothesis is proposed:

Hypothesis 3c: The market risk has a negative effect on firm innovative performance in clusters.

As already indicated, apart from simply analysing separately the direct effects of these assumed influential variables, interaction effects between them are likewise investigated. By focussing on the interactions between the firm-level, cluster-level and industry-/market-level, and thereby following a suggested ‘interactionist approach’ (e.g. Beugelsdijk, 2007), the firm performance differentials within clusters can be explained from an even broader perspective.

3. Data and Methodology

For the empirical investigation of the multilevel conditions necessary to profit, in terms of innovative performance, from the specialized labour within clusters, various data sources and variables are taken into consideration. The main database for the analysis is an extensive firm-level database provided by the Stifterverband. This database is based on a large representative survey, taking place in a two-year rhythm (“full survey”), of all designated R&D-active firms in Germany between 1995 and 2015. The Stifterverband primarily collects this comprehensive innovation-related information in the survey for the Federal Ministry of Education and Research in Germany (Engel et al., 2016; Schneider and Eckl, 2016; Stifterverband, 2018).[7] Building on this database, the dependent variable for firm innovativeness can be calculated as 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). Due to the lagged nature of the underlying survey question as well as the clear distinction between innovation

[7] For a good overview about the concrete advantages of this database (e.g. detailed information) compared to accounting data, see for example Schmid et al. (2014).

outputs and inputs in the overall survey design, it is argued that reverse causality is not a major concern in this study (Hervas-Oliver et al., 2018).[8] In comparison with patents, which are frequently used as proxies for firm innovativeness, this indicator offers two main advantages. First, the innovative output of companies that do not patent their product innovations is here also considered. Second, the share of the firm´s product innovations in sales is a market-driven indicator, so that 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). It is therefore argued that the share of the firm´s product innovations in sales is, compared to patents, the more appropriate dependent variable for the purpose of this study.

The database provided by the Stifterverband is additionally used to determine several independent variables. In line with the previously presented theoretical insights (e.g. De Saá-Pérez and García-Falcón, 2002; Hatch and Dyer, 2004), the human resource capabilities are measured by dividing the average R&D personnel expenses from 1997 to 2013 (including legal personnel costs as well as pension grants, gratifications and training costs) by the average internal R&D expenditures. The derived indicator, representing the average share of R&D personnel expenses in the total internal R&D expenditures, is believed to capture adequately the most important aspects of human resource capabilities. Furthermore, the gender diversity can also be calculated by employing the Stiftverband database. In accordance with other relevant studies in this field (Drach-Zahavy and Somech, 2001; Lorenzo et al., 2017; McGuirk and Jordan, 2012), the Gini-Simpson index, also known as the Blau index, is used based on the average share of male and female R&D employees (1997-2013). The index is defined as

$$D_i = 1 - \sum_i p_i^2 \qquad (1.)$$

in which p is the proportion of the total population in each gender category (female and male). The Gini-Simpson index D_i ranges thereby from zero (no diversity) to one (maximum diversity). If the entire R&D workforce is for example male, then D_i equals zero. A higher value of D_i therefore means more diversity or, in other words, a greater spread across the two considered categories (McGuirk and Jordan, 2012). In order to calculate the gender diversity of the labour pool within clusters, the estimated firm diversity is aggregated on the corresponding cluster-level and then divided by the number of firms in the cluster. Moreover, for the measurement of the stock of human resources of the cluster, the average number of

[8] As a first robustness check, an explicit time lag structure has been additionally implemented in the corresponding empirical models by calculating the dependent variable only for the years 1999-2013, while changing the previous reference period of the independent variables to 1997-2011. The corresponding results thereby remain basically the same and can be provided upon request.

firms' employees within the corresponding cluster (between 2008 and 2013) is calculated.
The information about human resources collected in the standard survey since 1995 has however been extended in the year 2013. With its special focus on human capital, this extended part of the survey contains even more information about additional characteristics of R&D personnel (e.g. professional qualifications and the exchange of scientific R&D personnel) (Schneider and Eckl, 2016). It therefore creates the basis for further independent variables such as the degree of overlap between the overall labour qualifications within the cluster and the labour qualifications of the firms. Based on the share of different qualification subjects (e.g. engineering as well as medicine and health services), labour qualification profiles for the firms and the clusters are first of all estimated. The labour qualification profiles of the clusters are constituted by the average labour qualification profiles of all firms located in the corresponding clusters. In order to finally measure the degree of overlap, the cosine index is calculated.

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

The cosine index determines the similarity between the two vectors A (firm´s labour qualification profile) and B (cluster labour qualification profile) for n qualification categories. In this case, seven different labour qualification categories are considered. The final index can take a value between zero and one, where one means perfect similarity or in other terms a perfect degree of overlap between both labour qualification profiles. The extra information from the extended survey of the Stifterverband is additionally used to estimate the human capital exchange intensity. Here for, the sum of the shares of the scientific R&D expatriates and inpatriates in the total number of scientific R&D personnel is calculated. Moreover, the data from the extended Stifterverband survey from 2013 is also utilized for estimating the matching capacities of the labour pool within clusters, as it offers information about the coverage of the staffing needs. In particular, the matching capacity of the labour pool is proxied by the share of clustered companies that expect to cover their need for scientific R&D employees in the next three years. In line with other contributions (e.g. Erikson and Lindgren, 2009), the average share of R&D employees with a PhD or a habilitation is additionally calculated for each cluster as a proxy for the quality of the labour pool within the corresponding clusters.

Apart from the Stifterverband database, further data sources are employed. Patents, retrieved from the European database PATSTAT, are for example used to estimate the pace of technology evolution of the corresponding industry. Despite well-discussed drawbacks

(e.g. Griliches, 1990), patents have been frequently applied as proxies for industry-specific technological advances (Audretsch and Feldman, 1996; Haupt et al., 2007; McGahan and Silverman, 2001). The average technological improvement (measured by the weighted number of patents) in three-digit NACE Rev. 2 code industries is computed for a two-year period (2012-2013) in order to control for possible outliers. By subsequently dividing the average technological improvement by the size of the corresponding industry, measured in terms of the average number of employees, the final indicator for the pace of technology evolution is also weighted by the industry size. Furthermore, based on data about industry revenue provided by the German Federal Statistical Office, the pace of market evolution can be determined. Similar to the volatility index (e.g. Dreyer and Grønhaug, 2004), the pace of market evolution is here calculated by the rate of change (between 2012 and 2013) of the revenue in three-digit NACE Rev. 2 code industries.[9] As indicated in the literature (e.g. Suarez and Lanzolla, 2007), both the pace of technology and market evolution additionally affect the overall market risk. Consequently, market risk is estimated by the interaction term between the pace of technology and market evolution.

Since the empirical analysis is primarily concentrated on companies within clusters, it is essential to determine these regional clusters adequately. For the identification of all relevant clusters in Germany, this paper therefore applies the method of Brenner (2017). Based on official IAB[10] employment data from 2012 in three-digit NACE Rev. 2 code industries, a cluster index for each single company on the community level ("Gemeindeebene") is calculated accordingly. In comparison with more traditional cluster indicators, the actor-based approach by Brenner (2017) offers two main advantages. First, the Modifiable Area Unit Problem (MAUP) can be avoided, because the cluster identification by Brenner (2017) is free of predefined borders. Contrary to other approaches, the unit of analysis are individual actors and their exact geographical location. Consequently, the applied cluster identification does not depend on the regional level. Second, by using a distance decay function based on travel times[11] to consider the geographical distance to all other firms of the same industry as a weight to the final cluster index, a possible overvaluation of one very large company can be avoided (Brenner, 2017; Scholl and Brenner, 2016). Apart from the geographical distance, the cluster index used here additionally considers employment in absolute and relative terms. Thus, it accounts explicitly for geographical proximity, regional concentration and specialization being the most central elements of cluster definitions (Grashof, 2017). Following the procedure of the European Cluster Observatory, a value of 2 is employed as

[9] As a further robustness check, both variables have also been tested for a different time period (between 2011 and 2013). Thereby, the corresponding empirical results remain stable.
[10] The Institute for Employment Research (IAB) is the research unit of the Federal Employment Agency in Germany. For more information please see https://www.iab.de/en/ueberblick.aspx.
[11] In line with the literature, 45 minutes are seen here as an adequate limit for close geographical distance (Brenner, 2017; Scholl and Brenner, 2016).

the corresponding cluster threshold, indicating whether a firm is located in a cluster or not (European Cluster Observatory, 2018; European Commission, 2008). Since the applied cluster index captures the geographical distance as well as the spatial concentration on the firm-level, it is additionally useful for identifying the firm´s position within a cluster. High values of the actor-based cluster index illustrate thereby that firms are located in the centre of a cluster, whereas low values indicate that they are far away from clusters (Brenner, 2017). Based on the cluster index of all companies located in clusters, the above median[12], representing a value of 2.86, is calculated in order to create a dummy variable for the firm´s centrality within the corresponding cluster.

Further control variables have additionally been included to account for other factors that might influence firm innovative performance in clusters. To control for firm-specific influences, firm age (years since foundation), firm size (measured by the average number of employees between 2008 and 2013) as well as the company structure (dummy variable illustrating whether firms are independent and do not belong to a corporate structure) are added. Moreover, at the cluster-level, based on the number of unemployed workers on the community level ("Gemeindeebene"), the aggregated unemployment in each cluster is computed for the year 2013. By employing the German research directory ("Research Explorer"), containing comprehensive information on over 25,000 university and non-university research institutes in Germany, the number of research institutes within each cluster is additionally calculated (Research Explorer, 2018). Lastly, to control for further industry-specific influences, a dummy variable is included capturing the research-intensity of industries, as it is assumed that particularly research-intensive industries tend to create innovations, especially radical innovations (Grashof et al., 2019; Tödtling et al., 2006).

Due to data protection regulations[13], all external data sources (e.g. cluster index and patent data) could however not be directly matched with the main database provided by the Stifterverband.[14] Instead as an intermediate step, all external data sources had to be matched with the AMADEUS[15] database offered by Bureau van Djik (BvD). Therefore, four different matching algorithms (Token, N-Gram, Soundex and Token-Soundex) were applied, each providing a similarity score between two strings (in this case company names). By using four different matching algorithms, potential weaknesses of each single algorithm can be offset, thereby improving the overall matching quality (Raffo, 2017; Raffo and Lhuillery, 2009). Additionally, the derived name couples of all four matching algorithms were also

[12] The median value has been chosen rather arbitrarily. However, other frequently applied thresholds, such as the mean and the 75th quantile, have also been tested. The corresponding results thereby remain quite robust and can be provided upon request.
[13] For further information on this issue please review the terms of use available under https://www.stifterverband.org/fdz.
[14] This is, however, a rather typical problem when using individual firm data (e.g. Mairesse and Mohnen, 2010).
[15] Indeed, a combination between AMADEUS and ORBIS databases is used in order to cover preferably all listed firms in Germany.

checked manually by the author to further ensure the quality of the matches. With the unique firm identifier (BvD ID), included in both datasets, the final merged data set could then be achieved. This unique firm-level database, combining several data sources, finally consists of 11,500 firms in Germany, of which 1,396 firms are located within a cluster. In line with previous contributions (e.g. Beaudry and Breschi, 2003; Rigby and Brown, 2015) and in order to reduce a potential measurement error bias created by year-to-year variability being ubiquitous in micro-level data (Rigby and Brown, 2015; Stern, 2010), the average values of the dependent as well as independent variables are used in an OLS regression. The OLS regression of the across panels´ averages is thereby actually the same as the between estimator, which is particularly useful to determine the effect of x when x changes between companies (Cameron and Trivedi, 2005; Gould, 2019). By averaging each observation i over t = 1,…T, the following equation can be obtained (Cameron and Trivedi, 2005):

$$\bar{y}_i = \alpha + \beta\bar{x}_i + (\alpha_i - \alpha + \bar{\varepsilon}_i) \tag{3.}$$

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 $\bar{\varepsilon}_i = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_{it}$.

In view of the hierarchical nature of the final database, an OLS regression with cluster correction of the standard errors is conducted. This methodical approach is more adequate in this context than a standard OLS regression, whose standard errors would be underestimated due to the given nested data structure (McNeish, 2014; Moulton, 1990). A multilevel regression would be another reasonable option (Cheah, 2009; Rabe-Hesketh and Skrondal, 2012). However, Likelihood-ratio tests indicated no significant statistical improvements compared with an OLS regression with cluster correction. Thus, it can be stated that the selected methodical approach is adequate to answer the underlying research question of this paper.

4. Empirical results and discussion

The descriptive statistics for all main variables of the cluster sample are presented in table 1. The observations for four variables are much lower than for the rest of the variables. This can be explained by the limited data availability for these four variables in the representative extended database from 2013 provided by the Stifterverband (Schneider and Eckl, 2016). Despite the unavoidable lower number of observations, the corresponding analyses are appropriate[16], especially in light of missing alternative datasets.

[16] The corresponding empirical models in table 3 exceed the minimum number of observations (between 10 and 20 observations per covariate) suggested by Harrell (2001).

Table 1: Descriptive statistics of all main variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Innovativeness	1396	8.256	14.490	0	100
Age	1373	45.600	41.632	0	355
Independence dummy	1396	0.035	0.184	0	1
Human resource capabilities	1389	0.665	0.113	0.106	1
Gender diversity	1396	0.397	0.171	0	1
Centre position in cluster	1396	0.500	0.500	0	1
Human capital exchange intensity	166	0.171	0.971	0	11.538
Firm size	1396	1297.389	15562.18	0	460388
Degree of overlap	208	0.820	0.296	0	1
Stock of alliances within cluster	1391	0.064	0.186	0	4.658
Diversity of the labour pool within cluster	1396	0.397	0.103	0	1
Stock of human resources of the cluster	1396	159.980	1101.207	1.375	38728.05
Matching capacities of labour pool within cluster	206	0.209	0.226	0	1
Quality of labour pool within cluster	149	14.022	11.330	0	50
Unemployment in cluster	1386	1373.387	2681.416	4	31288.57
No. Research institutes	1396	4.580	14.721	0	85
Pace of tech. evolution	1396	1.723	2.683	0	18.399
Pace of market evolution	1295	1.010	0.043	0.626	1.190
Market risk	1295	1.801	2.854	0	20.793
Research-intensive industry	1396	0.452	0.498	0	1

By further examining the correlations between the independent variables, some cases could be identified which might potentially suffer from multicollinearity.[17] Therefore, the Variance Inflation Factor is estimated for each model. However, the results indicate that indeed in no case any of the Variance Inflation Factors come close or even exceed the standard critical value of 10 (Belsley, 1991; Myers, 1990; Stevens, 2002). Consequently, it can be stated that multicollinearity is not a significant concern in this study.[18]

Moreover, in the context of empirical studies dealing with clusters, one frequently stressed concern is the existence of a selection bias, meaning that especially above-average innovative companies are located within clusters. Nevertheless, following the argumentation by McCann and Folta (2011), such a positive selection effect cannot be theoretically nor

[17] The corresponding pairwise correlation matrix for all independent variables of the cluster sample is presented in table 5 in the appendix.

[18] Nevertheless, in some models certain independent variables are excluded in order to prevent any kind of multicollinearity, thereby further increasing the stability of the model estimates of the coefficients in the end.

empirically justified. For example, Shaver and Flyer (2000) present evidence for an adverse selection, indicating that due to knowledge spillovers, benefiting more rather weak innovative companies than the strong ones, very innovative companies have high incentives to avoid co-location in clusters. Furthermore, for the main empirical analysis, concentrating on explaining the heterogeneity within clusters in terms of firm innovative performance, such a bias is argued to be rather irrelevant.[19]

Before starting with the main analysis, based on the full sample and by using an OLS regression with robust standard errors, it is checked whether a cluster effect on firm innovativeness can really be found. In line with previous empirical findings (e.g. Baptista and Swann, 1998; Bell, 2005; Grashof, 2018), the corresponding results indeed show that being located in a cluster has a significant positive influence on firm innovativeness.[20] Nevertheless, it is assumed here that this positive influence of clusters is not equally distributed among firms. In accordance with Hervas-Oliver et al. (2018), the subsample of clustered firms is therefore analysed in order to identify the specific conditions under which firms can gain from the cluster environment, in particular from the specialized labour pool (see table 2 and table 3). Table 2 tests some of the main formulated hypotheses. Model 1 represents the baseline model. Except for firm age, being only significant in the baseline model, all other control variables remain the same throughout all models. In model 2, human resource capabilities, gender diversity and the centre position in the cluster core are additionally added. As assumed, for all three firm-specific variables, a significant positive effect on firm innovativeness in clusters can be asserted. This means that firms need to own sufficient human resource capabilities in order to identify, acquire and train the best talents from the specialized labour pool within clusters. Moreover, the results also provide evidence for a stimulating influence from gender diversity within the firm´s stock of R&D employees, which can be seen as a fountain for new diverse ideas and capabilities. Furthermore, due to a potentially higher visibility and status gains, the location in the core of the cluster also significantly fosters firm innovative performance. In model 3, two supplementary cluster-level variables are included. Regarding the stock of human resources of the cluster a small, however, very significant impact can be determined, indicating that the higher supply of specialized labour in clusters makes the matching and search processes of firms more efficient. Therefore, empirical evidence is provided for the principal rationale of the economies of agglomeration (e.g. Arthur, 1990). Similarly, for the diversity of the labour pool within clusters, a positive influence on firm innovative performance can likewise be detected. Thus, the gender diversity is not only on the firm-level an influential contextual variable, but

[19] As shown by the standard deviation in table 1 as well as in figure 1 in the appendix, the innovative performance of firms located in clusters is indeed characterised by relatively high differences.
[20] The results are presented in table 7 in the appendix.

also on the cluster-level.

Table 2: OLS regression with clustered standard errors of single cross-section average over time (sample with cluster companies)

Innovativeness (sample with cluster companies)	*Model 1 n = 1.363*	*Model 2 n = 1.356*	*Model 3 n = 1.356*	*Model 4 n = 1.262*	*Model 5 n = 1.262*
Firm-level variables					
Gender diversity		10.949***			
		(2.869)			
Human resource capabilities		11.084**	11.152**	10.330**	10.172**
		(4.384)	(4.347)	(4.709)	(4.743)
Centre position in cluster		1.917**	1.942**	1.455*	1.537*
		(0.872)	(0.861)	(0.850)	(0.846)
Cluster-level variables					
Stock of human resources of the cluster			0.001***	0.002***	0.002***
			(0.000)	(0.000)	(0.000)
Diversity of the labour pool within cluster			8.894**	8.966**	9.809**
			(4.325)	(4.094)	(4.075)
Market-/Industry-level variables					
Pace of technology evolution				0.547***	5.558**
				(0.206)	(2.178)
Pace of market evolution				-1.037	8.435
				(8.337)	(7.604)
Market risk					-4.830**
					(2.045)
Control variables					
Age	0.015*	0.006	0.014	0.007	0.007
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Independence dummy	-1.552	-1.832	-1.613	-0.901	-1.067
	(1.724)	(1.769)	(1.687)	(1.590)	(1.537)
Number of research institutes in cluster	-0.002	-0.007	-0.004	-0.013	-0.017
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Unemployment in cluster	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Research-intensive industry dummy	3.084***	3.428***	3.285***		
	(0.906)	(0.854)	(0.877)		
Firm size	0.000*	0.000*			
	(0.000)	(0.000)			
Constant	*6.236****	*-6.065**	*-5.755**	*-3.396*	*-13.478*
R^2	*0.0237*	*0.0491*	*0.0411*	*0.0420*	*0.0468*

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

Model 4 introduces the pace of technology and market evolution. Contrary to hypothesis 3a, the pace of technology evolution asserts a significant positive impact on firm innovative performance in clusters. Hence, evidence is found that under a rapid technology evolution, firms rather promote product innovations in order to potentially avoid an erosion of their existing competitive advantage. The fast-changing technology developments offer in this context a relatively high opportunity of creating these new product innovations, as existing value chains are reshaped (Zhou et al., 2005). Regarding the pace of market evolution,

however, no significant influence on firm innovativeness in clusters can be ascertained, so that hypothesis 3b cannot be confirmed. In model 5, the market risk, being an interaction term between both paces, is additionally analysed. As assumed, the market risk asserts a negative impact on firm innovativeness, meaning that a high market risk significantly reduces the innovativeness of clustered firms. One plausible explanation here for is that the human resource decisions, frequently containing large sunk costs (Ernst and Viegelahn, 2014; Schaal, 2017), are likely to be postponed, which in turn decreases potential gains derived from the specialized labour pool in clusters.

In light of the unavoidable smaller number of observations related with the extended Stifterverband survey from 2013, the corresponding results are presented separately in table 3.[21] Model 6 in table 3 shows the results for the degree of overlap between the overall labour qualifications within the clusters and the labour qualifications of the corresponding firms. In accordance with hypothesis 1c, evidence is found that a high degree of overlap between both labour qualification profiles significantly increases firm innovative performance.[22] Hence, for firms it is beneficial to possess a human resource stock with similar skills compared to the overall cluster. Moreover, model 7 contains the human capital exchange intensity. The corresponding results suggest a positive, however, insignificant impact of the human capital exchange intensity on firm innovativeness in clusters. Hypothesis 1d can therefore not be confirmed. In model 8, the influence of the matching capacities of the labour pool within clusters is additionally analysed. It can be shown in this context that the matching capacities of the labour pool have a significant positive effect on firm innovativeness.[23] In other words, clusters with a relatively well functioning labour pool, in terms of matching labour supply and demand, offer a more beneficial environment for firm innovative performance than clusters with a rather poorly functioning labour pool. Hypothesis 2d can therefore be confirmed. The last model of table 3 investigates the relationship between firm innovativeness in clusters and the quality of the labour pool within clusters. Contrary to hypothesis 2c, the quality of the labour pool within clusters has a significant negative influence on firm innovativeness in clusters.[24] Being located in a cluster with a relatively high share of scientific R&D employees with a PhD or a habilitation is therefore rather inhibitory to firm innovativeness compared with lower degrees such as a Master or Bachelor. Therefore, evidence is provided that the role of scientific degrees should not be overemphasized as in general clusters with lower university degrees offer a more conducive context for firm innovativeness. In light of previous studies

[21] The results have been verified by using single year values for the dependent variable (from 2013 or 2015) as well as short-term averages (from 2011 to 2013). The corresponding results can be provided upon request.
[22] The existence of a potential inverted u-shaped pattern has also been tested. However, no evidence is found for such a pattern.
[23] The coefficient becomes even more significant ($p = 0.034$), when it is only analysed together with the control variables. The corresponding results can be provided upon request.
[24] Similar to the matching capacities, the significance of the coefficient of the quality of the labour pool within clusters even increases ($p = 0.047$) when it is only examined together with the control variables. The corresponding results can be provided upon request.

(e.g. Vinding, 2006), the results are at first sight quite surprising.

Table 3: OLS regression with clustered standard errors of single cross-section average over time (sample with cluster companies based on the extended survey focussing on HR)

Innovativeness (sample with cluster companies)	*Model 6 n = 205*	*Model 7 n = 163*	*Model 8 n = 162*	*Model 9 n = 121*
Firm-level variables				
Degree of overlap	15.879*** (4.092)	17.360*** (4.384)		
Human capital exchange intensity		3.745 (3.311)	3.542 (3.260)	3.895 (3.441)
Cluster-level variables				
Matching capacities of labour pool within cluster			10.501* (6.226)	
Quality of labour pool within cluster				-0.241* (0.139)
Control variables				
Age	-0.035 (0.028)	-0.055* (0.029)	-0.070** (0.031)	-0.066** (0.032)
Independence dummy	-8.840** (3.837)	-8.022** (4.035)	-11.559*** (4.119)	-8.775* (4.967)
Number of research institutes in cluster	-0.016 (0.094)	-0.042 (0.096)	-0.066 (0.097)	-0.047 (0.103)
Unemployment in cluster	-0.001** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001** (0.000)
Research-intensive industry dummy	7.418** (2.839)	6.674** (3.155)	5.256** (3.075)	4.916 (3.385)
Constant	*10.876***	*11.458***	*25.232****	*30.201****
R^2	*0.1021*	*0.1282*	*0.0896*	*0.1073*

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

But, by analysing the specific operationalization of other variables used in this context, it becomes obvious that most studies group all university degrees as being the highest qualification level (López-Bazo and Motellón, 2018; Pfeifer and Wagner, 2014; Vinding, 2006). By comparing this rather large group with other groups, such as those having a high-school diploma, these studies come to the conclusion that a high share of qualified employees asserts a significant positive impact on firm innovativeness. However, in view of an increasing qualification trend in Germany (Baethge and Wolter, 2015), resulting in more and more university graduates, and the underlying focus on R&D-active firms, this study takes a different approach, separating between the various university degrees (e.g. Bachelor, Master as well as PhD and habilitation).

Apart from the direct effects of the firm-level, cluster-level and industry-level variables, it is assumed that there exist potential interaction effects between the three levels of analysis. Consequently, several interaction effects have additionally been investigated. The most interesting results are presented in table 4. In line with Lee et al. (2001), the corresponding interaction terms are added one by one in order to prevent multicollinearity problems. Model 10 tests whether the stock of human resources of the cluster moderates the effect of firm's human resource capabilities. The underlying assumption is that in clusters with a large labour pool, it is not necessary for firms to strengthen their human resource capabilities, as it is easier for them to find and acquire the right candidate due to the higher supply of specialized labour. As indicated by the corresponding significant negative interaction term, evidence is indeed found that high human resource capabilities are not beneficial in clusters with a large labour pool. Instead, companies should rather increase their R&D expenditures in other areas, such as R&D material resources, in order to avoid an inefficient distribution of their limited resources towards high human resource capabilities. Furthermore, in model 11 it is tested whether the effect of human resource capabilities on firm innovativeness differs between the centre and the periphery positions in clusters. It is reasonable to assume that due to a lower visibility especially in the periphery of a cluster, human resource capabilities are required to find and acquire the most adequate talents. The corresponding empirical results indeed show a negative, however, insignificant interaction effect between the human resource capabilities and the centre position in clusters. Consequently, no statistically significant differences can be found in this context.

Nevertheless, by investigating the interaction effect between the stock of human resources of the cluster and the position in clusters, statistically significant results can be determined. The results, presented in model 12, indicate that particularly companies located in the core of the cluster can gain from a large stock of human resources of the cluster. One plausible explanation here for is that central companies located in the cluster core can, due to their higher visibility, attract much easier the most talented candidates from the large labour pool compared with companies located in the periphery of a cluster. The thirteenth model tests the potential interaction effect of the human capital exchange and the centre position in the cluster core. Evidence is found for a significant positive interaction effect on firm innovativeness in clusters, meaning that especially in the centre of a cluster, firms need to have a sufficiently large human capital exchange intensity. Since these central firms possess a more intensive internal connection (Grashof, 2018), such a sufficiently large human capital exchange intensity seems to be necessary to avoid a potential lock-in situation. Similar to the results of Boschma et al. (2009), focussing on labour mobility and plant performance, it can hence be asserted that the human capital exchange per se does not have a significant

influence on firm innovativeness, but it rather depends on the concrete circumstances whether such an exchange is beneficial for firm innovativeness.[25]

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

Innovativeness (sample with cluster companies)	*Model 10 n = 1.356*	*Model 11 n = 1.356*	*Model 12 n = 1.356*	*Model 13 n = 163*	*Model 14 n = 146*
Firm-level variables					
Human resource capabilities	12.291*** (4.402)	15.856*** (5.679)	11.468*** (4.368)		-29.577 (27.850)
Gender diversity		10.902*** (2.856)	9.951*** (2.898)		
Centre position in cluster		8.250 (5.532)	1.513* (0.894)	-0.930 (5.532)	-1.170 (3.713)
Human capital exchange intensity				-15.318 (6.309)	
Cluster-level variables					
Stock of human resources of the cluster	0.008*** (0.001)		-0.001 (0.001)		
Diversity of the labour pool within cluster	11.098** (4.327)				
Quality of labour pool within cluster					-1.668** (0.754)
Interaction terms					
Stock of human resources of the cluster x Human resource capabilities	-0.014*** (0.003)				
Human resource capabilities x Centre		-9.713 (8.327)			
Stock of human resources of the cluster x Centre			0.003*** (0.001)		
Human capital exchange x Centre				21.988*** (7.328)	
Quality of labour pool within cluster x Human resource capabilities					2.189** (1.088)
Control variables					
Age	0.014 (0.009)	0.005 (0.008)	0.004 (0.009)	-0.063** (0.030)	-0.060* (0.032)
Independence dummy	-1.634 (1.684)	-1.737 (1.775)	-1.604 (1.691)	-9.556 (5.748)	-6.949 (5.866)
Firm size		0.000* (0.000)		-0.000 (0.000)	0.000 (0.000)
Number of research institutes in cluster	-0.007 (0.024)	-0.008 (0.024)	-0.006 (0.025)	-0.058 (0.096)	-0.010 (0.105)
Unemployment in cluster	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.000 (0.000)
Research-intensive industry dummy	3.637*** (0.900)	3.473*** (0.844)		4.292 (3.059)	7.297** (2.931)
Constant	*-6.250**	*-9.232***	*-4.030*	*28.522****	*47.019***
R^2	*0.0417*	*0.0503*	*0.0424*	*0.0984*	*0.1050*

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

[25] Boschma et al. (2009) suggested considering the types of skills that flow into a plant and/or company in this context. Due to data constraints this has not been possible with the applied database. However, future studies may further concentrate on this issue.

The last model of table 4 investigates a potential interaction effect between the quality of the labour pool within clusters and the human resource capabilities of a firm. The results show that the corresponding interaction term has a significant positive influence on firm innovative performance in clusters. Thus, it can be argued that, while in general asserting a negative effect, when owning sufficiently high human resource capabilities, firms can indeed benefit from a high quality of the labour pool within clusters, as they are capable of fully exploiting such an environment.

5. Conclusion

All in all, the results indicate that, on the one hand, in accordance with Baptista and Swann (1998), being located in a cluster increases on average firm innovativeness. But on the other hand, companies located in regional clusters do not gain equally and in the same manner from the specialized labour pool in clusters. Instead there exist several conditions, from different levels of analysis, that are necessary to profit from the specialized labour pool.

On the firm-level, it has been shown that particularly the gender diversity, human resource capabilities, the centre position in the cluster core as well as the degree of overlap between the labour qualifications within the cluster and the labour qualifications of the firms are significant determinants of firm innovative performance in clusters. For managers it is therefore essential to consider these four firm-specific variables so that they can evaluate and adapt better their current situation in order to realize the potential advantages of the specialized labour pool in clusters. In addition, they should also take possible interaction effects into account. For example, even though the human capital exchange intensity by itself asserts no significant impact, it does in the case of a centre position in clusters. For companies located in the cluster core, it is thus beneficial to possess a relatively high human capital exchange intensity in order to avoid a possible lock-in situation, which is more likely in the cluster core due to its pronounced internal linkages (Grashof, 2018).

Although not directly influenced by companies, the cluster-level should also be taken into account. Despite the direct positive effect of the stock of human resources of the cluster, the diversity of the labour pool within clusters and the matching capacities of the labour pool within clusters as well as the direct negative effect of the quality of the labour pool within clusters, they also interact with firm-specific variables. For example, in clusters with a large labour pool, it is suggested that it is not efficient for firms to strengthen their human resource capabilities, as it is easier for them to acquire the right candidates due to the relatively high supply of specialized labour. Moreover, evidence is found that especially companies located in the centre of the cluster can gain from such a large labour pool due to their higher visibility,

easing the attraction of the most talented candidates. Additionally, firms particularly need to have sufficiently large human resource capabilities in a high quality labour pool in order to be capable of exploiting the existing opportunities of such a high quality labour pool in clusters.
Lastly, variables from the market-/industry-level have also been shown to be relevant determinants of firm innovative performance in clusters. Surprisingly, the pace of technology evolution, with its increasing technological pressure to innovate and its extensive opportunities for innovations, creates a promoting context for firm innovativeness in clusters. Nevertheless, in a situation characterized by a rapid technology and market evolution, the innovativeness of firms is inhibited. Such a high market risk is argued to delay or even reject human resource decisions, decreasing in turn the potential gains from the specialized labour pool in clusters.

For policy makers it also seems to be important to take the derived results into account so that the recent criticism about the one-size-fits-all orientation of most cluster policies, focussing primarily on collaborative incentives, can be effectively addressed (Uyarra and Ramlogan, 2017; Tödtling and Trippl, 2005; Vicente, 2014). As proposed by Auer and Tödtling (2017), cluster policies should rather focus on the concrete conditions and needs within clusters in order to improve the efficiency of such measures. In this context, the results of this paper can serve as a first profound guideline for the identification of potential problems and needs that policy can concretely target so that more companies can gain from the specific cluster environment, which in turn increases the overall performance within clusters due to interrelations and knowledge spillovers (McCann and Folta, 2008; Shaver and Flyer, 2000).

In spite of these interesting and extensive results, there exist, however, some limitations to this study. Due to data constraints[26], especially regarding the calculation of the cluster index for several years, the study applied an OLS regression with clustered standard errors to a single cross-section of variables average over time (between estimator). Historically, such an approach has been criticized due to a concern that omitted variables, represented by the individual effects, may be correlated with the independent variables. In other words, this would mean that there exists a correlation between the error term and the explanatory variables that leads to inconsistent estimates. However, such a potential bias also holds true for other approaches.[27] Additionally, such a bias constitutes only one of several possible misspecifications of such models (Baltagi, 2005; Hauk Jr. and Wacziarg, 2009; Mairesse and Sassenou, 1991; Stern, 2010). In light of the underlying research question focusing more on

[26] A regression on a balanced panel data set would result in a significant loss of observations, as the underlying questions of the dependent as well as independent variables are only inconsistently answered over the years (50% of the firms respond only four times during the period under investigation). For further information on this issue, see also Mairesse and Mohnen (2010).
[27] The results of the omitted variable tests performed here, however, indicate that such a bias is not a mayor concern in this study.

the between-variation as well as the available data, it is thus argued that the chosen methodical approach is appropriate despite its limitations in contrast to panel-regressions (Griliches and Mairesse, 1984; Hauk Jr. and Wacziarg, 2009; Kafouros, 2008).[28] Nonetheless, for future studies it may be promising to fully exploit panel-data so that dynamic effects can also be investigated. This holds particularly true for the dynamic evolution across the cluster life cycle (e.g. Menzel and Fornahl, 2010) and potential impacts on the sustainability of firm innovative performance in clusters. Since detailed information about the employees (e.g. from which company they come) is missing within the used database, for subsequent studies it may also be interesting to utilize a linked employer-employee dataset (e.g. provided by the IAB in Germany[29]) with which questions related to the labour movements within regional clusters can be addressed specifically. Additionally, the empirical setting of this study is limited to Germany, eliminating the risk of unobserved effects by country-specific differences in the corresponding institutational environments (López-Bazo and Motellón, 2018). Nevertheless, future research may expand the analysis by taking countries from diverse economic development levels into account so that potential country-specific effects can also be investigated.

However, despite these limitations, it can be resumed that the empirical results contribute to closing a still ubiquitous research gap regarding firm performance differentials in clusters. Contrary to the prevalent assumption of equal gains within clusters, it can be shown that depending on multilevel conditions and their interplay, firms profit differently from the specialized labour pool in clusters. Furthermore, the findings provide a practical value especially for managers as well as policy makers, because they can better evaluate under which conditions it is more likely to realize the potential advantages of the specialized labour pool in clusters and where more efforts have to be invested in order to improve the present situation.

[28] It is indeed very common for empirical studies using innovation surveys to predominantly exploit cross-sectional data, instead of panel-data (Mairesse and Mohnen, 2010).

[29] For further information on this dataset please review the corresponding IAB website available under https://fdz.iab.de/en/Integrated_Establishment_and_Individual_Data/LIAB.aspx.

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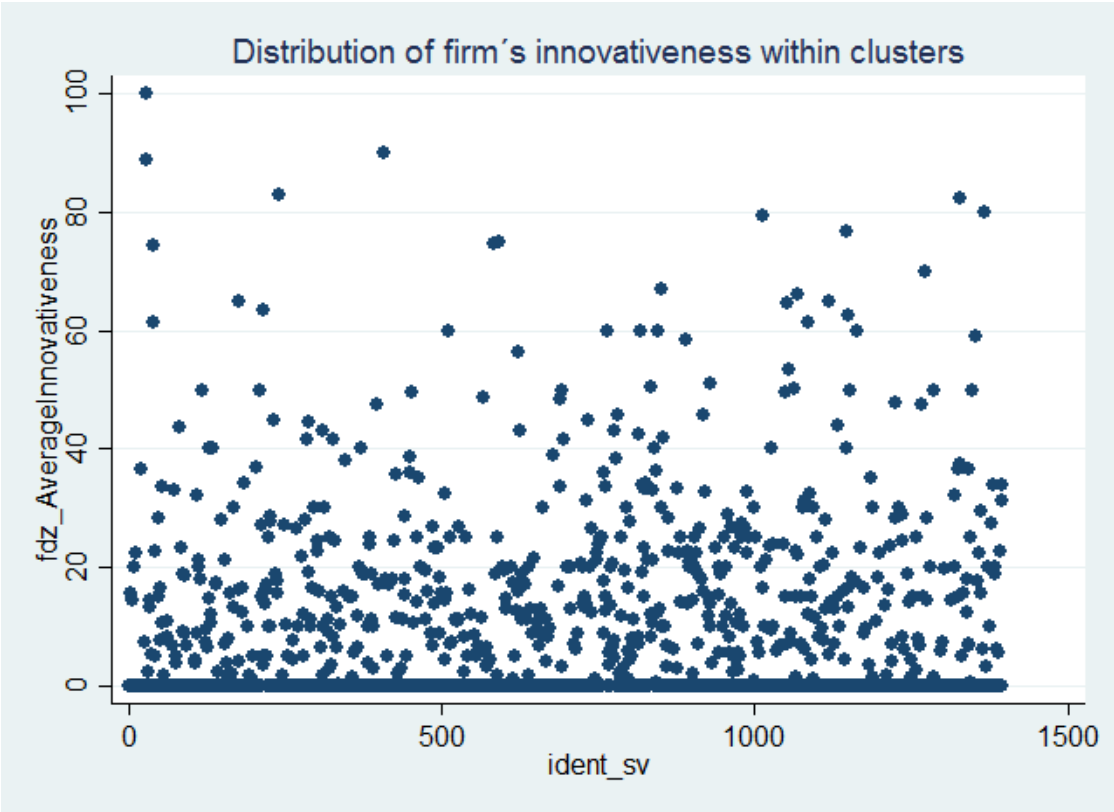
Appendix

Table 5: 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.	17.	18.
1. Age	1.000																	
2. Independence dummy	0.104*	1.000																
3. HR capabilities	0.003	0.011	1.000															
4. Human capital exchange	-0.035	-0.007	-0.054	1.000														
5. No. Research institutes	-0.055*	-0.006	0.091*	-0.026	1.000													
6. Pace of tech. evolution	-0.046	-0.002	0.093*	0.019	0.027	1.000												
7. Pace of market evolution	-0.035	0.004	0.043	0.008	0.082*	0.134*	1.000											
8. Market risk	-0.044	-0.005	0.093*	0.128	0.028	0.997*	0.161*	1.000										
9. Research-intensive industry	-0.079*	-0.009	0.034	-0.073	-0.008	0.548*	0.042	0.514*	1.000									
10. Centre position in cluster	-0.033	-0.020	-0.024	-0.043	-0.122*	0.076*	-0.001	0.078*	-0.010	1.000								
11. Degree of overlap	-0.132	-0.102	0.086	0.044	-0.030	-0.124	-0.124	-0.129	-0.205*	-0.074	1.000							
12. Gender diversity	0.213*	0.050	-0.039	-0.128	0.070*	-0.130*	0.020	-0.122*	-0.136*	0.032	-0.176*	1.000						
13. Matching capacities of labour pool	0.168*	0.094	-0.033	0.071	0.034	-0.048	-0.071	-0.034	-0.183*	-0.044	0.180*	0.068	1.000					
14. Stock of HR of the cluster	0.066*	0.008	-0.073*	0.001	0.022	-0.014	0.000	-0.016	0.085*	0.018	-0.060	0.055*	0.023	1.000				
15. Diversity of the labour pool	0.137*	0.049	-0.073*	-0.084	0.080*	-0.215*	0.033	-0.200*	-0.226*	0.055*	-0.154*	0.604*	0.136	0.091*	1.000			
16. Firm size	0.119*	0.023	-0.067*	-0.011	0.017	-0.006	0.002	-0.008	0.058*	0.016	-0.228*	0.079*	0.002	0.807*	0.067*	1.000		
17. Unemployment in cluster	-0.011	0.002	-0.020	-0.042	0.041	0.006	-0.092*	0.011	-0.064*	0.008	0.052	0.035	0.114	0.029	0.058*	0.018	1.000	
18. Quality of labour pool	0.008	0.117	-0.079	0.117	0.026	-0.152	0.129	-0.138	-0.063	-0.093	-0.103	0.030	-0.018	0.147	0.179*	0.244*	0.047	1.000

Note: *p < 0.05

Figure 1: Variance of the innovativeness (sample with cluster companies)



Note: fdz_AverageInnovativeness: Firm innovativeness; ident_sv: Firm specific identifier

Table 7: OLS regression models with robust standard errors of single cross-section average over time (full sample)

Innovativeness (full sample)	*Model 1* *n = 11.228*
Cluster dummy	0.822** (0.418)
Age	0.004 (0.004)
Independence dummy	0.076 (0.661)
Human resource capabilities	16.626*** (1.527)
Gender diversity	7.001*** (1.089)
Number of research institutes	-0.032*** (0.006)
Pace of technology evolution	0.531*** (0.074)
Firm size	0.000 (0.000)
Constant	*-7.312****
R^2	*0.0317*

Robust Standard errors in parentheses.
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

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