Industrial and Corporate Change Advance Access published January 8, 2013

Industrial and Corporate Change, pp. 1–31
doi:10.1093/icc/dts043

Impact of local knowledge endowment on employment growth in nanotechnology

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This article investigates the contribution of local knowledge endowment to employment growth in nanotechnology firms. We exploit a unique data set focusing on firms operating in fields that apply nanotechnology. Our findings suggest that regions that offer knowledge can stimulate employment growth in smaller and younger firms. By contrast, being embedded into specialized regions might be counterproductive, especially for firms belonging to a particularly knowledge intensive sector and older firms.

JEL classification: D83, L25, O31, R11.

1. Introduction

All over the world, nanotechnologies are seen as the most promising future technology with a great economic potential for growth and employment. The term nanotechnology thereby refers to most different types of analysis and processing of materials, which have one thing in common: their small size (1–100 nm). Nanotechnology makes use of the special characteristics that many nanostructures do not only depend on the original material but very much also on their size and

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shape. It is widely accepted as being the next general purpose technology (e.g. Youtie *et al.*, 2008).

Nanotechnology is still a young and dynamic technology, there is large scope for improvement, and innovation activities are essential firm activities. In Germany, small and medium-sized enterprises (SME) account for more than 80% of all nanotechnology firms (Schnorr-Bäcker 2009). Owing to fragmented R&D and production processes, most of the firms only provide parts of complex value creation chains while being embedded in various networks. As a consequence of their high innovation intensity, the anchorage of the actors within regional specializations is central. One general expectation concerning the overall role of nanotechnology firms is their contribution to job generation thereby strengthening regional competitiveness. It is reasonable to assume that the characteristics of the economic surrounding feed back to nanotechnology firms' performance and vice versa.

Along this line of reasoning, this article addresses the impact of two economic key characteristics of nanotechnologies and their potential for job creation and growth: as *high technology*, the usual arguments in the context of the proximity–productivity relationship, i.e. the linkages between innovation, spillovers, and economic performance also apply to nanotechnology. Especially important are hence not only firm specificities but also a sufficiently specialized surrounding to translate spillovers to actual productivity gains. Key determinants are thus a sufficiently high overlap of firms' activities (absorptive capacity) and the availability of qualified labor. Consequently, the actors' regional anchorage and especially the composition of regional labor markets are central determinants of success.

In contrast to this is the *general purpose character* of nanotechnology, which basically allows introducing the technology in any context. This implies that a certain degree of regional specialization is not mandatory per se, but, depending on the state of development of the technology, even the contrary may the case: too narrow regional specialization patterns may inhibit the technology's use in a multitude of application fields, thereby possibly suppressing potential opportunities for cross-fertilization and innovation-enhancing feedback mechanisms across diverse and so far unrelated value creation chains.

This is the starting point of the article at hand. It addresses two major questions: (i) (How) do firm-specific and location-specific characteristics interact and influence the process of job creation of nanotechnology firms? and (ii) What is the impact of regional specialization in this context? Put differently, which characteristic of nanotechnology predominates its character as a high technology [i.e. being located in a sufficiently specialized region thereby benefitting from regional (knowledge) spillovers is of major importance] or the character as a general purpose technology (according to which opportunities aside from already-existing specializations may be more important for firm success)? The empirical analysis is based on an online survey carried out in 2011 among German nanotechnology firms. The regional levels are German Raumordnungsregionen, i.e. official statistical units used in Germany lying between NUTS2 and NUTS3. We apply a two-step regression approach starting with ordinary least squares (OLS) and subsequently followed by a fixed-effect panel regression to analyze how nanotechnology firms' employment growth is affected by both firm-specific and location-specific determinants. In doing so, we especially link the analysis to existing specialization patterns. Our main results may be summarized as follows: location of nanotechnology firms matters for employment growth. However, the relative importance of the degree of specialization of the economic surrounding decreases in favor of diversification. This might be interpreted as an indication of the relevance of the general purpose character of nanotechnology. The remainder of the article is as follows: in Section 2, we supply the theoretical background and derive our main hypotheses (Section 3). Section 4 introduces our methodology and data. In Section 5, we present our results and interpretations, and Section 6 briefly concludes.

2. Related literature

There is a vast literature on firm growth referring to sales, revenues, or employment. Most prominent determinants underlying the analyses are the characteristics of the firm (e.g. size, age, industry affiliation, financing strategy), of the entrepreneur (e.g. education, skill distribution), or firm location (e.g., Storey, 1994, for an overview). Related theories range from neoclassical considerations on optimal size (Coase, 1937), over internal learning-by-doing processes (Penrose, 1995) and evolutionary concepts in which the "fitness" of firms plays a central role (e.g. Coad, 2007) to the socio-economic view, which highlights the importance of resource availability and the competition for these resources (e.g. Uhlaner *et al.*, 2007). Empirical findings suggest that there is not one single key determinant driving firm growth, but the result is highly context specific and depends on the interaction of several influencing factors (e.g. Harhoff *et al.*, 1998; Delmar *et al.*, 2003; Coad, 2007).

Independent of the studied determinants, country, or sector, the literature unambiguously highlights the positive relationship between innovative activity and firm growth (e.g. Acs and Audretsch, 1988; Del Monte and Papagni, 2003; Adamou and Sasidharan, 2007; Harrison *et al.*, 2008; Coad and Rao, 2008). The studies also stress the overall importance of employment and the availability of qualified labor for innovation (e.g. Acs and Audretsch, 1990; Pianta, 2005; López-García and Puente, 2009).

Feldman (1994) or more recently Feldman and Kogler (2010) provide evidence that especially innovative activity tends to cluster thereby pointing to the importance of specialization; at the same time, several studies show that firms in clusters reach higher levels of innovation (e.g. Moreno *et al.*, 2004; Fromhold-Eisebith and Eisebith, 2005). Of special interest are the characteristics of local knowledge, thereby suggesting that specialized local knowledge has a particularly positive effect on innovation and firm growth (Feldman and Audretsch, 1999). Fritsch and Slavtchev (2008, 2010) also confirm that innovating firms are not isolated, self-sustained entities but rather highly linked to their environment. Location matters, as it may provide access to specialized networks of firms, suppliers, institutions, or labor (see also Porter, 2000; more critically Martin and Sunley, 2003). Other arguments discussed in the context of clustering include stronger pressure to innovation or lower costs for innovation commercialisation (Ketels, 2009). Spillover opportunities and thus the proximity–productivity linkage decrease with distance, as knowledge that is highly contextual most frequently requires interaction and face-to-face contact (von Hippel, 1994).

However, until recently there are only few studies that analyze the role of location and the proximity–productivity relationship for post-entry performance, i.e. the growth of firms (e.g. Gabe and Kraybill, 2002; Boschma and Weterings, 2005; Audretsch and Dohse, 2007; Weterings and Boschma, 2009). The concept of regional clusters systematically picks up this proximity–productivity relationship systematically thereby relying on specific economic activities and has become a popular policy measure. Although a cluster always refers to a specialized network of firms and institutions, there is no finally accepted definition of industrial clusters. Porter's considerations, however, might be seen as representing the standard concept (Martin and Sunley, 2003). Porter (2000: 254) defines cluster as "geographically proximate group of inter-connected companies and associated institutions in a particular field that is linked by commonalities and complementarities". As a positive external knowledge spillover, they increase their productivity and economic performance. There is evidence that firms in clusters reach higher levels of innovation (Moreno *et al.*, 2004; Fromhold-Eisebith and Eisebith, 2005). The basic reasoning behind specialization or industry-specific advantages being relevant for the efficiency of local innovation activity implies that local agents can share the same assets and can benefit from goods and services provided by specialized suppliers as well as from a local labor market pool (Marshall, 1890). The cluster environment provides not only a stronger pressure to innovate but also a richer source of relevant knowledge and ideas as well as lower costs for innovation commercialization (Ketels, 2009). Cluster strength is hence considered a determinant of prosperity differences across space. As a clustered industry indicates that there are significant benefits from co-location, the industry's productivity is assumed to increase with the level of specialization within the cluster. In the light of this, knowledge diffusion will occur when firms are embedded in more specialized environment (Marshallian externalities) or in regions that are more diversified (Jacobian externalities). More precise, the assumed relevance of clusters hence refers to the characteristics of local knowledge and suggests that specialized local knowledge has a particularly positive effect on innovation and firm growth. We contribute to this literature by extending the basic question of the impact of specialized local knowledge endowment (both *amount* and *composition*). In doing so, our research focuses on nanotechnology firms' growth. This is particularly challenging, as this young technology is not only innovation and therefore knowledge intensive but is also coined by a general purpose character. Thus, the relationship between regional specialization and firm growth is not per se clear in the discussed context.

Our article is most closely related to Audretsch and Dohse (2007) who find that regions abundant in knowledge resources provide a particularly fertile soil for the growth of young, technology-oriented firms. They consider new market firms and point to the need of investigating the relationship between local knowledge endowment and firm performance in other high and emerging technologies. Our unique data set on German nano firms allows us to test their main hypotheses in the promising field of nanotechnology. Although Audretsch and Dohse (2007) only elaborate on the influence of the accessible stock—and hence the quantity—of local knowledge, we extend the analysis to the *composition* and hence the quality of the local knowledge base. Besides, we test the robustness of our hypotheses by two different econometric approaches and introduce novel measures that expand their explanatory power.

3. Derivation of hypotheses

Following the argumentation earlier in the text, we propose the natural expectation that location characteristics do affect the growth of firms in nanotechnologies. We moreover assume that employment growth in nanotechnology firms is strongly related to successful innovative activity. Following Feldman (1994), knowledge spillovers (from closely related external factors and knowledge sources) are especially relevant for small firms, as the resources necessary to maintain the knowledge base are typically beyond their means. The new growth literature hence finds a propensity for knowledge inputs and spillovers to agglomerate, and therefore it can be reasonably assumed that firms that are in fact using knowledge inputs, such as firms in high-tech or innovation-intensive industries, will perform better once they are located in a high-density region, as these firms will have better access to knowledge resources and knowledge spillovers. Hence, characteristics of location seem to preserve and even reinforce an innovating firm growth. However, until recently, little effort has been done to analyze the role of location and its economic characteristics for post-entry performance, i.e. the growth of firms (Audretsch and Dohse, 2007). The importance of agglomeration and the impact of spatial proximity on firm performance have only been studied recently (e.g. Gabe and Kraybill, 2002; Audretsch and Dohse, 2007; Weterings and Boschma, 2009). Following Audretsch and Dohse (2007: 100), who find that regions abundant in knowledge resources provide a particularly fertile soil for the growth of young, technology-oriented firms, we carry out such an analysis, also focusing on the special role of locational characteristics for the growth of firms in high-tech, particularly nanotechnology-applying industries. However, we will go one step further by considering the composition of local knowledge agglomeration. We therefore suggest that the extent to which external knowledge is crucial and can be absorbed differs widely across different firm size classes and knowledge-intensive sectors. In doing so, we pay attention to the characteristics of the structure of the region a firm is located in (so-called location characteristics) and the knowledge processing characteristics of the firm itself. We suggest that the impact of location characteristics on employment growth in nanotechnology differs across firm size classes, knowledge intensive sectors, and age groups (see description in section 4.3). We therefore hypothesise that:

> *H1: Location characteristics do influence the employment growth of firms in nanotechnology. In particular, the impact of location characteristics on specific knowledge-intensive sectors, firm size, and firm age classes matters here.*

Put differently, we hence suppose that regions rich in knowledge provide a particularly good environment for the growth of technology-oriented, i.e. knowledge-intensive firms. Taking into account the peculiarities of nanotechnologies as general purpose technology (GPT) and the interaction with the characteristics of location, the arguments suggest that specialization might not be conducive for the employment growth of firms that are active in the exploration of general purpose nanotechnologies, as this hampers the inflow of knowledge from other fields and even suppresses positive effects stemming from diversity and nanotechnologies' application in a wide variety of fields. Catalyzing knowledge recombination and fertilizing ideas from other application fields most presumably cannot be processed in an environment with a single focus. However, firms experience a tension when they aim to advance and exploit existing knowledge and at the same time explore new fields simultaneously (Leten *et al.*, 2007). Therefore, local specialization seems to be necessary to develop sufficiently strong capabilities in particular domains to be able to realize economies of scale in technology development while incrementally advancing the technology. Hence, local specialization effects might have a positive effect on growth in nano firms: firms that are not particularly intensive in knowledge are assumed to rather exploit existing knowledge. We therefore separate the analyses again. The smaller and the younger a firm is, the more we assume it to be prone to specialization externalities owing to the fact that small firms are often highly specialized and enter the market via specialized niches (van der Panne, 2004). As the exploration of the field is intensive in knowledge, we moreover assume that knowledge-intensive, exploring firms are particularly benefiting from diversity, and hence specialization might have a negative impact. Given the GPT nature of nanotechnology and the chances that are inherent in diversity and exploration of the field and on the other hand the minimum degree of knowledge in the respective field needed to be able to keep up with leading edge development, we assume that too less and too much regional specialization negatively influence firm performance in either of the firm classes we distinguished. We suggest that local specialization effects (see description in Section 4.3) have a negative impact on nanotechnology firm growth. Put another way, the effects of the co-location of the distinct industry the nanotechnology firm belongs to negatively impact the development of the firm, as it restrains the growth opportunities across diverse fields that nanotechnology, being a general purpose technology, offers. Having stated this conjecture, we hence hypothesize that the feature of nanotechnology, being a GPT, outweighs the benefits local specialization is found to inhere for the growth of high-tech firms in general means.

> *H2: Local specialization effects impacts the employment growth of firms in nanotechnology negatively. (i) Although specialization has a direct negative impact on employment growth in particularly knowledge-intensive firms and older firms, (ii) too much local specialization hampers employment growth in general.*

Finally, we analyze the robustness of the impact of specialization effects and location characteristics on employment growth. Thus, we investigate whether the yearly changes of the level of specialization might interfere with the yearly changes in the growth rates. In this context, we hence more technically assume that:

> *H3: Specialization effects that are related to average employment growth are the same as those that are related to a year-to-year consideration of employment growth.*

The expected results will sharpen our understanding of the association between concentrated activity of firms and the corresponding performance in the field of nanotechnologies as an emerging GPT. They may serve as a starting point for regional policy aiming at the improvement of the regional factors influencing the growth of firms in growth-promising nanotechnologies.

4. Methodology and data

4.1 Data source

In our unique data set, we focus on firms operating in fields that develop or apply nanotechnology. That means that we investigate firms that are concerned with nanotechnology in any possible way, be it basic R&D or the employment of nanotechnology in later stage of the value creation chain, irrespective of whether this is their main field of activity. These firms are not only knowledge intensive by operating in a high-tech sectors, but particularly because nanotechnologies are still in a nascent stage of development, and hence these firms are intensive in innovation—which is by definition knowledge intensive. However, nanotechnology firms operate across a wide range of industries and are therefore particularly heterogeneous in nature, e.g. referring to SIZE, KIS and AGE. This is why we investigate one the one hand all firms together and on the other hand have to construct different subsample across these characteristics. Our data set of firms consists of records from the “competence atlas nanotechnology in Germany” (www.nano-map.de), an online database providing information on firms that are concerned with nanotechnologies. We then conducted an online survey in 2011, asking the firms for information on employment numbers for different years, profits, year of foundation, zip code, and their industry affiliation (i.e. NACE classification of the 2-digit and 3-digit industry affiliation) on the basis of their main products. This is particularly necessary because nanotechnology as GPT does not constitute a single industry, but is present in a wide range of different industries. In all, 216 of 1950 contacted firms answered, which gives a response rate of 11.1%. The non-response bias (respectively *t*-test) is a commonly used method (e.g. Wooldridge, 2010) to ensure whether our firm sample is not prone to sample selection. We run a *t*-test for the two groups of interest, i.e. early and later answering firms, the latter ones representing the firms that will never provide a response. The corresponding *P*-values are non-significant for both, the number of employees and the profits, indicating that our firm sample is representative of the entire population. In doing so, the independent samples *t*-test compares the difference in the means from the two groups with a given value (usually 0). In this vein, we split our firm sample into two groups: (i) response at an early stage (first wave of survey) and (ii) response at a later time (second wave of survey). The *t*-test statistics obviously show that there are neither in the case of number of employees nor in the case of profits significant differences between the two groups. The results indicate that there is no statistically significant difference between the mean values for the first wave and the second wave of survey ($t = 1.1866$, $P = 0.2371 > 0.05$). In other words, the firm sample is not prone to sample selection. The level of analysis within our survey is the geographical level of planning regions ("Raumordnungsregionen"). Germany consists of 97 planning regions. This level is chosen, as it is particularly suited to approximate spatial and functional interrelations between core cities and the corresponding hinterland [Bundesamt für Bauwesen und Raumordnung (BBR) 2001]. Therefore, they are homogeneous and comparable entities, which are large enough to assume that spillovers are intraregional, and hence no connection between the different regions has to be included in our estimations (Audretsch and Dohse, 2007). It has to be mentioned that the nano firms in our sample are not equally distributed: of the 97 planning regions, the nanotechnology firms in our sample are located in 62 different regions, some of them hosting a multitude of firms.[1] Figure 1 displays this distribution. The data for the regional part of the analyses, i.e. mainly the employment data for the corresponding planning regions, come from the Federal Employment Agency (Bundesagentur für Arbeit), statistics of employees subject to social insurance contributions and from the Federal Office for Building and Regional Planning [BBR, Indikatoren und Karten zur Raum- und Stadtentwicklung in Deutschland und in Europa (INKAR)].

[1]In all, 62 different regions: average 3.8; max 18; and min 1.

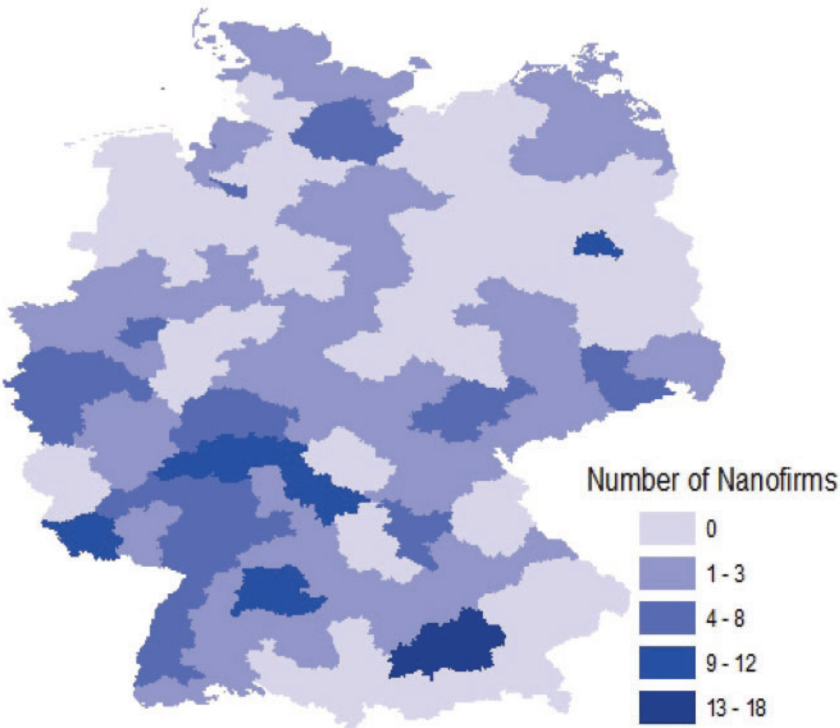

Figure 1 Distribution of answering nano firms across Germany.

4.2 Dependent variable

Before starting with the regressions, an operationalization of the term firm growth is necessary. There is a wide range of definitions that deal with firm growth. Garnsey et al. (2006: 11) suggest that "firms' growth can be measured in terms of input (e.g. employees), in term of value of the firm, and in terms of output (e.g. turnover, profit)." In our analyses, we use the growth measure of the growth of employees. We hence define our dependent variables by measuring the log form of employment growth as the ratio of the year t (respectively 2010) to year t-1 (respectively 2006). The variable values for the year of the financial crisis, 2008, were replaced by the average (i.e. mean value) of the other available years' values. More precisely, it might be that the stochastic properties of the growth rates exhibit entirely different growth features as in the other years of the studied period. In other words, growth events (i.e. growth rates) during the financial crises (respectively 2008) seem to occur with a significantly higher probability to follow extreme growth events. Nevertheless, in some cases number of employees is completely missing for all years. Hence, we are not able to replace these missing values.

4.3 Explanatory variables

Regarding our hypotheses, we use several independent variables. These variables display firm-specific and location-specific characteristics. The firm-specific variables reflect rather usual factors found to influence employment growth, such as firm size, age, and industry affiliation. Location-specific variables by contrast shall reflect the knowledge characteristics that are specific to the environment the firm is located in. An overview of the description of explanatory variables is given in Table 1, and the independent variables are discussed as follows:

1. *Firm-specific characteristics*

The *SIZE*-dummy controls for the size of the firm, as smaller firms more intensively and more frequently rely on knowledge spilling over for generating new knowledge and innovative activity than larger firms (Audretsch, 1998). We hence assume small and medium-sized firms (*SIZE* = 1) to benefit differently from location-specific characteristics than larger ones (*SIZE* = 0). *KIS* is an industry-dummy, indicating whether a firm belongs to a particularly knowledge-intensive sector within the sample (*KIS* = 1, *high-KIS*) (*KIS* = 0, *low-KIS*).[2] *KIS* is constructed by the share of "knowledge workers" in an industry's labor force, which is measured by the share of employees with a university degree. Sectors with an above-average share of knowledge workers are hence seen as knowledge intensive (see Audretsch and Dohse, 2007). We use this dummy to be able to distinguish between firms that are operating in above average knowledge-intensive industries among our sample of firms and hence especially prone to knowledge spillovers as positive externality raising their productivity. Moreover, *high-KIS* firms should be able to better incorporate, i.e. to use the knowledge that is spilling over, as it is widely accepted that firms that are themselves active in knowledge processing and production exhibit a high absorptive capacity (Cohen and Levinthal, 1990). We expect location, hence, to have a more relevant, positive influence on *high-KIS* firms. We investigate whether firm age (*AGE*) is an initial trigger for firm growth in nanotechnology. Age is consistently found to be a relevant impact factor on firm performance (Coad, 2010). As we assume that the impact of local knowledge characteristics on firm growth depends on firm characteristics, we use the modal age of the firms in our sample as cut-off point for creating a subsample of young and older firms each. Hence, we use *KIS*, *AGE*, and *SIZE* of nanotechnology in form of a dummy to be able to introduce different subsamples and investigate the particular role of location-specific characteristics, given differing firm-specific characteristics.

[2]Although it is natural to assume most of the firms in nanotechnologies to be intensive in knowledge as nanotechnologies definitely are considered as high tech, this is not what we expect from our data. We surveyed firms that are processing nanotechnologies in which way whatsoever. Subsequently, it might well be that the main activity of the firm is not in a high-tech sector.

Table 1 Description of explanatory variables

Category	Variable	Description
Firm-specific characteristics	SIZE	Small and medium enterprises, defined as those with less than 251 employees (SME = 1).
	KIS	Firms in sectors with an above-average share of employees with university degree are knowledge intensive (KIS = 1).
	AGE	Age of the firm in terms of years since foundation. Cut-off point used to distinguish between young and old firms is modal age.
Location- specific characteristics	HQ	Region exhibits a share of highly qualified employees with university degree in the top quartile.
	INDDENS	Measures industry density (employees in industry per km^2) in a region, catchall variable for agglomeration effects.
	IND	Absolute employment in the firms' industry in its region, pointing to the actual strength of the firm's industry in the considered region
	STUD	Absolute number of students in the considered region.
	R&D	Absolute number of employees in R&D in considered region.
	LQ	The location quotient (LQ) is calculated by the ratio of the share of employees of a region i in industry j, divided by the total share of employees in this very field in the whole country.

2. *Location-specific characteristics and the nature of the regional knowledge base*
The location-specific variables refer to the role of locations, particularly to possible knowledge spillovers generated in the region. With *HQ*, we introduce a region dummy referring to whether a region exhibits a share of highly qualified (*HQ*) employees in the top quartile, measured by employees with university degrees. The industry (IND) variable, by contrast, displays the absolute number of employment employees in the firms' industry in its region. In both, the *HQ* and *IND*, we hence implicitly assume that the regional human capital displays the regional knowledge resources, which is commonly done, as knowledge can be considered as incorporated in individuals who are able to process it (Rigby and Essletzbichler, 2002).[3] The distinction between these two variables is useful, as the *HQ* dummy is a relatively general measure of knowledge intensity in the region, whereas *IND* is more

[3]We hence subsequently treat human capital as proxy for knowledge resources, bearing in mind the remark by Audretsch and Dohse (2007) that although the interpretation of the average level of human capital in a region proxying local knowledge resources as part of the local firm's productions function is straightforward, it remains still abstract, as it lacks a mechanism by which human capital actually contributes to higher growth (see also Rauch, 1993).

specialized, pointing to the actual strength of the firm's industry in the considered region. We expect both to have a positive influence on firm growth. *INDDENS* by contrast is a catchall region-specific variable catching agglomeration effects in general by displaying the industry density (INDDENS) of a region to improve the model fit. It measures the number of industry employees subject to social insurance contributions per square metre in the respective region. A further standard measure capturing regional knowledge resources is the presence of a university in a region, as universities are at the same time supportive and necessary for regional innovation and economic development (Feldman and Kogler, 2010). Research results are open to the public and ready to be exploited as knowledge spillovers. We therefore use the absolute number of students (STUD) in a region. As we expect knowledge spillovers to increase with available knowledge resources, STUD should have a positive impact on firm growth. A similar argumentation holds for R&D, a variable displaying the share absolute number of employees mainly concerned with R&D in a region. The knowledge inherent in and produced by human capital (mainly) concerned with R&D is likely to be another source of knowledge spillovers. The specialization (Location Quotient, *LQ*) variable measures region-specific knowledge resources and refers to the characteristics of the knowledge within a region. It is constructed using employment data, corresponding to the industry in which the firm operates. Location quotient is calculated by the ratio of the share of employees of a region in the industry into which the nanotechnology firms classified itself, divided by the total share of employees in this field in the whole country:[4]

$$LQ_{i,j} = \frac{\frac{Employees\ in\ region\ i\ in\ industry\ j}{Employees\ in\ Germany\ in\ industry\ j}}{\frac{Employees\ in\ region\ i}{Employees\ in\ Germany}} = \mathrm{LQ}$$

LQ indices are usual measures for specialization externalities (Paci and Usai, 1999). For the empirical analysis, we use a standardization, making the index symmetric and easier to interpret by using the formula $LQ = 100^{*}\ (\mathrm{LQ}^2 - 1)/(\mathrm{LQ}^2 + 1)$, which constrains possible values within the interval (−100,100) (see Vollrath, 1991; Grupp, 1994). Values above 0 hence indicate an above average, values below 0 below average specialization. Following our hypotheses, we expect *LQ* to influence the growth of firms. Table 1 pictures the different explanatory variables and a short description of variables. In general, we distinguish between firm-specific characteristics (SIZE, AGE, and KIS) and locations-specific characteristics (HQ, INDDENS, IND, STUD, R&D, and LQ).

[4]Note that, for reasons of readability, LQ will be used instead LQ_ij.

Table 2 Firm-specific characteristics

Category	Subsample	Description	Frequency	Share
SIZE	SME	$1 \leq x \leq 250$	144	66.6
	Large sized	>250	72	33.4
KIS*	High-KIS (KIS = 1)	Above average share of R&D employees	178	82.4
	Low-KIS (KIS = 0)	Below average share of R&D employees	38	17.6
AGE**	Younger	≤8 years (modal age)	42	19.5
	Older	>8 years (modal age)	174	80.5

*Measure based on Audretsch and Dohse (2007).

**Cut-off point in terms of younger/older firms: Modal age of 8 years since foundation.

4.4 Descriptive statistics and stochastic properties

The final database consists of 216 firms. The descriptive statistics for the used variables are given in Table A1 (in the appendix). In respect to the different stochastic properties of the entire sample, the variables *SIZE*, *KIS*, and *AGE*[5] are hence used to distinguish between the different subsamples. Table 2 shows the number of firms differentiated by different firm size classes, knowledge-intensive sectors, and age groups.

Firms classified as SME are defined as those with less than 251 employees (European Commission 2003). Obviously, SME firms are overrepresented in our sample. However, this is in line with the overall distribution of firms across size, regardless of their technological background: actually, there are more SME than larger firms in nanotechnology. More particularly, nano firms are mostly SMEs and more seldom larger firms (Schnorr-Bäcker, 2009), which is why our sample represents the population well. Hence, the share of SMEs in the studied sample matches approximately the share in reality. Table 2 moreover shows the share of firms differentiated *KIS*[6] (i.e. the most knowledge-intensive sectors) and *AGE* (i.e. younger and older firms). Additionally, Table 2 pictures that our sample consists of an above average number of firms active in knowledge-intensive sectors (*KIS*). Finally, we distinguish our sample between younger and older firms. The cut-off point in terms of younger and older firms is represented by the modal age of 8 years

[5]A majority of previous research tends to emphasize that younger firms exhibit higher growth rates than their larger counterparts (Jovanovic, 1982) and firm growth decreases with firm age (Acs and Müeller, 2008; Coad, 2010). In this context, the discussion on different age groups becomes apparent. A challenging task is still the cut-off point in terms of younger and older firms.

[6]The firms in our sample operate across 10 different nanotechnology fields: average 2.1; max 7; and min 1.

(Huergo and Jaumandreu, 2004; Fagiolo and Luzzi, 2006). In this vein, the distinction between different age groups provides additional information on the growth process. To sum up, the firm sample operates across a wide range of industries and is therefore particularly heterogeneous in nature, e.g. referring to SIZE, KIS, and AGE. Therefore, we run independent group *t*-tests to test the different specifications (i.e. *SIZE*, *KIS*, and *AGE*) against each other. In the case of the different firm SIZE classes, the t-statistic is −2.4202 with 214 degrees of freedom. The corresponding two-tailed *P*-value is 0.0163, which is less than 0.05. The same is true for the different AGE classes, i.e. t-statistics is −2.6107 with 214 degree of freedom and a corresponding two-tailed *P*-value of 0.0097. Finally, we conclude that the difference of means in growth rates between SME/larger firms and younger/older firms is different from 0. Surprisingly, in the case of knowledge-intensive sectors (KIS = 1/KIS = 0), the mean difference of KIS = 1and KIS = 0 is not different from 0 (i.e. t = 0.0187; df = 214 and *P*-value = 0.9851). We are nevertheless convinced that these subsamples operate on different frequencies and are differently influenced by location-specific characteristics (see Audretsch and Dohse, 2007).

4.5 Regression approach and model fit

First, we set up a regression approach using OLS estimation (see equations 1 and 2) to analyze the average growth of firm. As independent variables, all the described variables are used. We use the standard regression approaches, as it can be expected that our residuals are approximately normally distributed. There is no evidence for a deviation from a normal distribution in our data. We also do not find other problems, such as heteroscedasticity for our regressions with the logarithm of relative growth as dependent variable. Reynolds *et al.* (1994) and more recently Audretsch and Dohse (2007) developed an estimation approach that includes location-specific determinants of growth, which we will build on for investigating whether firm growth in nanotechnology is affected by different location-specific characteristics. Again, we analyze the average growth effect of these independent variables. For our investigation, we run the log-level model. In the log-level model, $100^{*}\alpha_1$ is sometimes called the "semi-elasticity" of y with respect to x. (Wooldridge, 2010: 45). First, we primarily investigate the impact of indicators on the average growth (from 2007 to 2010) of employment. In our equations, *LOCATION* stands for the various measures of location-specific characteristics. In our case, we use *HQ*, *INDDENS*, *IND*, *STUD*, and *R&D*. We set up regressions for subsamples of different firm size classes (*SIZE*), knowledge-intensive sectors (*KIS*), and different age groups (*AGE*) all using the following model:

$$\left(\log(empl_{2010}) - \log(empl_{2007})\right)_j = a_o + \sum_{k=1}^{5} a_k LOCATION_{kj} + a_6 SIZE_j + a_7 AGE_j + a_8 KIS_j + \varepsilon_j \qquad (1)$$

Equation (1) shall preliminarily investigate whether former findings in the literature on the relationship between location characteristics (as discussed earlier in the text) and employment growth hold for the studied case. The employment of the specialization effect might catch some of these effects, which is why we analyze this basic model first. However, in equation (1), the degree of specialization of the local knowledge base is still neglected. As we assume that regional specialization has an influence on nano firm, we add the *LQ* measure as well as its squared term LQ^2. Thus, we investigate the impact of indicators on the average growth (from 2007 to 2010) of employment:

$$\begin{aligned}\left(\log(empl_{2010}) - \log(empl_{2007})\right)_j = a_o + a_1 LQ_j + a_2 LQ_j^2 \\ + \sum_{k=3}^{7} a_k LOCATION_{kj} + a_8 SIZE_j \\ + a_9 AGE_j + a_{10} KIS_j + \varepsilon_j\end{aligned} \tag{2}$$

Third, we analyze the robustness of the impact of specialization and location characteristics on employment growth. Thus, we change the perspective from *average growth* to a year-to-year consideration of growth. We investigate whether the yearly changes of the level of specialisation might interfere with the yearly changes in the employment growth rates. This means, if growth in 1 year depends on an increasing level of specialization or not, the relationship between current employment growth and previous specialization might be a direct effect or an indirect effect. As things stand, specialization effects are yet proved for average employment growth. Hence, it is not known whether specialization effects also occur for yearly changes (short-run consideration). It has also not been proven that year-to-year specialization effects do exhibit employment growth. To prove this, it would be necessary to disentangle this dynamic effect, we conduct a cross-sectional time-series model. Hence, we estimate firm growth using cross-sectional time-series estimation the fixed effects model. In particular, we run the model to gain a more detailed insight on individual characteristics that may contribute to the predictor variable and to control for unknown heterogeneity. More information on the panel dimension of the panel data and, specifically on, the time variation of each variable is given in Table A2 (in the appendix). To decide whether the fixed effects model is suitable (probably using random effects model), we perform the Hausman test. We do not fail to reject the null hypothesis and conclude that fixed effect model is appropriate ($\text{Prob} > \text{chi}^2$ is significant). To see whether time fixed effects are needed when running a fixed effects model, we run the joint test to see whether the dummies for all year are equal to 0 (i.e. if they are not, then time fixed effects are needed). We reject the null hypothesis that all year coefficients are jointly equal to zero, therefore time fixed effects are needed in the panel specification (i.e. $\text{Prob} > \text{F}$ is significant). Furthermore, we conduct one regression set for all firms together and then two other regressions for each of *SIZE*, *KIS*, and *AGE* subgroups separately. Hence, our equation (3) follows as:

$$\log(empl)_{it} = a_o + a_1 LQ_{it} + a_2 LQ_{it}^2 + \sum_{k=3}^{7} a_k LOCATION_{k,it} + c_i + \varepsilon_{it} \tag{3}$$

Finally, we test for multicollinearity (see appendix correlation matrix and VIF-test in Tables A3 and A4) and endogeneity. Moreover, we use the first year value in 2006 (or the first available value) of observation as independent variables in the case of H1 and H2. Some of our independent variables are correlated such as *HQ* and STUD ($r = 0.6294^{***}$) and *HQ* and *R&D* with $r = 0.5931^{***}$. *HQ* represents the share of highly qualified employees with university degree in the region that might be captured by *STUD* or *R&D*. Hence, we set up different regression models.

5. Results and interpretation

In the following section, we will discuss the main findings of the regression analyses and present the interpretation. The regression results are reported in Tables 3–5.

5.1 Location characteristics (Hypotheses 1)

As we want to especially gain information on the location characteristics that contribute to the growth of nano firms, we differentiate between the characteristics of the structure of the region a firm is located in. We preliminary assume that *location characteristics do influence employment growth of nano firms.* Furthermore, we suggest that *the impact of location characteristics on specific knowledge-intensive sectors, firm size, and firm age classes matters here.* The results for the regression analysis are presented in Table 3. In our analysis, we use the following location-specific characteristics (as described in Section 4.3): *HQ*, *INDDENS*, *IND*, *STUD*, *R&D*, and the control variables *SIZE*, *KIS*, and *AGE*. For some of the region-specific characteristics, we find significant results.

In the first step, we find significantly negative coefficients for the *AGE* of firms. This especially holds for the subsamples of all firms and smaller firms. Older firms are hence less likely to show higher growth than younger firms, which is in line with the findings of many other scholars before. It can be seen as “stylized fact” that growth tends to decline with firm age (Audretsch and Dohse, 2007). Older firms are characteristically more routinized, more inert, and less able to adapt (Coad, 2010). In contrast, we find a positive effect of *SIZE* for both age classes. Against the expectation that firm growth decreases as the firm becomes larger (stylized effect), we find a positive coefficient. The positive coefficients suggest that employment growth tends to increase as the firm becomes larger.

Table 3 OLS—employment growth (EMP): robust standard errors

Variables	(I) All firms EMP	(II) SME EMP	(III) Larger firms EMP	(IV) KIS = 1 EMP	(V) KIS = 0 EMP	(VI) Younger EMP	(VII) Older EMP
HQ	0.219** (0.0918)	0.198* (0.119)	0.233 (0.169)	0.250** (0.106)	−0.0415 (0.123)	0.540* (0.298)	0.143 (0.0906)
INDDENS	0.000164 (0.000733)	0.00121 (0.00116)	−0.00162 (0.00104)	−1.65e-05 (0.000872)	0.00104 (0.00109)	−0.000605 (0.00279)	6.25e-05 (0.000594)
IND	−1.85e-07 (3.20e-07)	5.69e-08 (3.48e-07)	−3.69e-07 (3.56e-07)	−1.08e-07 (3.13e-07)	−2.27e-05*** (6.99e-06)	−8.28e-06 (1.63e-05)	−1.55e-07 (3.37e-07)
STUD	−9.10e-07 (8.87e-07)	−1.21e-06 (1.23e-06)	−1.29e-06 (1.35e-06)	−8.60e-07 (9.30e-07)	−2.38e-06* (2.40e-06)	−1.84e-06 (3.66e-06)	−9.13e-07 (8.08e-07)
R&D	−4.48e-06** (2.05e-06)	−5.30e-06* (3.00e-06)	−4.84e-06 (3.43e-06)	−4.74e-06** (2.38e-06)	−3.66e-06 (3.18e-06)	−1.13e-05* (6.44e-06)	−2.90e-06 (1.97e-06)
SIZE	0.153*** (0.0556)			0.108 (0.0807)	0.143 (0.104)	0.345* (0.188)	0.105* (0.0610)
KIS	0.00526 (0.0577)	−0.0260 (0.0841)	0.0154 (0.0572)			0.0199 (0.186)	0.0111 (0.0637)
AGE	−0.0010*** (0.0004)	−0.00359* (0.00193)	−0.000127 (0.000458)	−0.000328 (0.000533)	−0.000635 (0.000623)		
Constant	−0.0114 (0.0668)	0.213** (0.0833)	0.110 (0.0960)	0.0289 (0.106)	0.220 (0.137)	−0.128 (0.235)	0.0156 (0.0668)
Observations	216	134	72	171	35	42	174
R-squared	0.063	0.056	0.101	0.060	0.464	0.171	0.033

Standard errors in parentheses.

***$P<0.01$, **$P<0.05$, *$P<0.1$.

Table 4 OLS with LQ variables—employment growth (EMP): robust standard errors

Variables	(I) All firms EMP	(II) SME EMP	(III) Larger firms EMP	(IV) KIS = 1 EMP	(V) KIS = 0 EMP	(VI) Younger EMP	(VII) Older EMP
LQ	−0.000928* (0.000524)	−0.000572 (0.000863)	−0.000819 (0.000652)	−0.00104* (0.000626)	0.000428 (0.000742)	−0.000812 (0.00190)	−0.00113** (0.000564)
LQ^2	−4.61e-06 (8.39e-06)	−3.87e-06 (1.27e-05)	2.41e-06 (9.29e-06)	−7.83e-07 (1.02e-05)	−1.56e-05 (1.08e-05)	−7.17e-06 (2.91e-05)	−4.54e-06 (8.70e-06)
HQ	0.219** (0.0910)	0.196* (0.118)	0.246 (0.173)	0.265** (0.105)	0.00931 (0.148)	0.544 (0.353)	0.138 (0.0895)
INDDENS	6.70e-05 (0.000755)	0.00113 (0.00119)	−0.00167 (0.00108)	−0.000152 (0.000894)	0.000884 (0.00103)	−0.000793 (0.00290)	−5.39e-05 (0.000618)
IND	−1.38e-07 (2.57e-07)	3.81e-08 (4.15e-07)	−2.17e-07 (3.77e-07)	−9.55e-08 (2.52e-07)	−2.38e-05** (9.06e-06)	−5.63e-06 (1.73e-05)	−1.24e-07 (2.74e-07)
STUD	−4.40e-07 (8.98e-07)	−8.38e-07 (1.37e-06)	−1.02e-06 (1.31e-06)	−3.43e-07 (9.75e-07)	−2.99e-06 (2.46e-06)	−9.66e-07 (4.18e-06)	−4.63e-07 (8.20e-07)
R&D	−4.34e-06** (2.12e-06)	−5.40e-06* (3.01e-06)	−4.46e-06 (3.53e-06)	−4.54e-06* (2.47e-06)	−4.78e-06 (3.53e-06)	−1.12e-05 (6.85e-06)	−2.51e-06 (2.05e-06)
SIZE	0.141** (0.0549)			0.101 (0.0800)	0.103 (0.104)	0.346* (0.203)	0.0903 (0.0596)
KIS	0.00194 (0.0580)	−0.0325 (0.0835)	0.0251 (0.0608)			0.00574 (0.241)	0.0102 (0.0639)
AGE		−0.00327 (0.00204)	−7.73e-05 (0.000467)	−0.000226 (0.000530)	−0.000662 (0.000723)		
Constant	−0.00283 (0.0715)	0.214** (0.0880)	0.0693 (0.113)	0.00380 (0.112)	0.298** (0.140)	−0.133 (0.243)	0.0239 (0.0735)
Observations	215	134	71	170	35	42	173
R-squared	0.075	0.059	0.130	0.075	0.502	0.176	0.054

Standard errors in parentheses.

***$P<0.01$, **$P<0.05$, *$P<0.1$.

Table 5 Fixed effects model (incl. time-fixed effects) for employment growth (EMP)

Variables	(I) All firms EMP	(II) SME EMP	(III) Larger firms EMP	(IV) KIS = 1 EMP	(V) KIS = 0 EMP	(VI) Younger EMP	(VII) Older EMP
LQ	−0.00231 (0.00178)	−0.00284 (0.00214)	0.00425 (0.00278)	−0.00296 (0.00195)	0.00376 (0.00565)	0.00133 (0.00811)	0.000602 (0.00163)
LQ^2	−2.83e-05* (1.64e-05)	−3.79e-05* (1.98e-05)	3.24e-05 (2.37e-05)	−3.16e-05* (1.75e-05)	2.30e-05 (5.99e-05)	−0.000143* (8.53e-05)	3.36e-06 (1.46e-05)
INDDENS	−0.00192 (0.00894)	−0.00801 (0.0134)	−0.00228 (0.00725)	−0.00385 (0.00985)	−0.00371 (0.0233)	−0.000430 (0.0430)	−0.00210 (0.00700)
IND	−2.70e-05 (2.72e-05)	−6.34e-05 (3.99e-05)	−3.29e-05 (2.41e-05)	−1.20e-05 (3.01e-05)	−0.000143** (6.87e-05)	−2.53e-06 (0.000164)	−4.24e-05** (2.12e-05)
_Iyear_2008	0.106*** (0.0181)	0.138*** (0.0260)	0.0482*** (0.0160)	0.104*** (0.0205)	0.132*** (0.0394)	0.153** (0.0749)	0.0939*** (0.0146)
_Iyear_2009	0.109*** (0.0177)	0.151*** (0.0245)	0.0188 (0.0162)	0.111*** (0.0201)	0.101*** (0.0368)	0.191** (0.0744)	0.0841*** (0.0143)
Constant	5.130*** (0.470)	3.576*** (0.640)	9.076*** (0.463)	5.120*** (0.504)	5.824*** (1.433)	3.033 (2.496)	5.753*** (0.361)
Observations	652	429	223	538	114	131	521
R-squared	0.116	0.158	0.070	0.114	0.192	0.163	0.135
Number of id	222	150	76	184	38	47	175

Standard errors in parentheses.

$^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$.

More important in the context of our concern is the impact of *HQ* representing the knowledge intensity in the region. The positive and significant coefficients of highly qualified employees (*HQ*) in the region on the employment growth of all firms point out that firms exhibit higher growth in regions characterized by a share of highly qualified employees in the top quartile. However, this finding does not hold for all subgroups and varies across different firm size classes, *KIS,* and *AGE* groups. Actually, the coefficient of *HQ* is significantly positive in smaller firms but not in larger. Thus, the impact of *HQ* in the region is especially relevant for smaller firms. This might be owing to the fact that larger firms are not as much depending on external knowledge and on possible knowledge spillovers stemming from high local endowments in knowledge, as they benefit from internal economies of scale in knowledge production, as their own knowledge stock is larger. Looking at the results of firms that belong to a knowledge-intensive industry (i.e. *KIS* = 1), we also find a strongly positive significant coefficient. This means firms with high knowledge intensity experience higher employment growth in regions with access to highly qualified employees, which is intuitive. Otherwise and in the case of low-knowledge industry (*KIS* = *0*), the coefficient shows no longer a significance. This seems similarly plausible, as these firms do not rely as much on knowledge activities, and hence regional knowledge endowment is not particularly important. Furthermore, we find another interesting issue concerning the impact of *HQ* (model VI and VII). We find a positively significant coefficient for firms that are younger than 8 years, but the coefficient is insignificant in case of older firms. This suggests that younger firms experience higher employment growth if they have access to qualified knowledge workers in their region. This finding also goes in line with the general findings by Dosi *et al.* (1995), and it even more emphasizes the relevance of possible knowledge spillovers for new firms that are entering or just entered the nanotechnology market and its relevance for success in the beginning phase where fundamental knowledge is gained.

Interestingly, in the case of low-*KIS,* growth is moreover even negatively influenced by the size of the group of employees that work in the same industry they are engaged in (*IND*). As the numbers of employees in the same industry also proxies the strength of regional competition, it might especially affect those firms negatively that do not profit as much as others from the positive effects of this concentration, such as (intra-industry) knowledge spillovers.

Let us now look at the results for the independent variable of *R&D* representing the absolute number of R&D employees in the region. As things stand, we derive negative and statistically significant coefficient of *R&D* for SME, knowledge-intensive sectors (*KIS* = 1) and younger firms, indicating that average employment growth tends to decline with a higher share of R&D employees in the region. Although this result might be counterintuitive in the first place, it could be a hint to what we will investigate in our second hypothesis: it is not knowledge per se that positively influences firm growth, *but* the influence of knowledge and the potentially resulting spillovers depends on the characteristics of the available knowledge. The kind of R&D processed might be too basic or to incoherent to be beneficial for firms that are interested in commercialization. For instance, Frenken *et al.* (2007) as well as Boschma and Iammarino (2009) refer to such an issue, when they argue that for knowledge to spill over effectively, and hence contribute positively to a firm's performance, related variety in form of complementarities among industries and their knowledge is necessary.

To sum up, our expectations (Hypothesis 1) are strongly confirmed by our results. We confirm that location characteristics can stimulate the growth of firms in nanotechnology. Besides typical impact factors such as *AGE* and *SIZE*, the share of highly qualified employees (*HQ*) does play a major role. We moreover obtain the result that the impact of *HQ* on firm growth varies across firm size, knowledge-intensive industries, and age groups. This means, in turn, that the share of highly qualified employees is more important in smaller firms than in larger firms, and seems to be more relevant in firms that are active in particularly knowledge-intensive industries. Simultaneously, the impact of *HQ* is more decisive in younger firms. We therefore set up a more precise Hypothesis 1, suggesting that "While the share of highly qualified employees is more important in smaller and younger firms as well as in firms belonging to a particularly knowledge intensive industry, a high share of R&D employees in the region has no positive impact on non-knowledge-intensive and older firms." Hence, we mostly confirm the findings in the literature that young, small, and knowledge-intensive firms with access to a high density of knowledge workers do experience an above average growth (Audretsch and Dohse, 2007). Thus, nanotechnology firms innovate and grow as other highly knowledge-intensive firms do, regardless of the peculiarities a GPT implies. Moreover, nanotechnology firms rely as much on knowledge spillovers as other high-tech (but not GPT) firms from other industries. Finally and most simply, the location-specific measures indicate that the growth of firms in nanotechnology is affected by their location-specific characteristics.

5.2 Specialization of the regional knowledge base (Hypotheses 2)

Remember, we suppose that regions that provide knowledge enrich the growth of technology-oriented, i.e. knowledge-intensive firms. As the extent to which external knowledge is crucial and can be absorbed differs widely across different firm size classes and knowledge-intensive industries, Hypothesis 2 states that (*i*) *specialization has a direct negative impact on employment growth in particularly knowledge-intensive firms and older firms*, whereas (*ii*) *too much local specialization hampers employment growth in general*. Moreover, we assume a non-linear impact and character of *LQ*. As you can see in Table 4, the independent variable of interest is *LQ*, representing the extent of regional specialization. Moreover, we also included LQ^2 to be able to control for non-linear effects of specialization. Additionally, we differentiate our sample into different firm size classes (*SIZE*), knowledge intensity (*KIS*), and age groups (*AGE*).

As model I in Table 4 shows, the coefficient of *LQ* does appear significant with a negative sign. This clearly indicates that specialization in any application field of general purpose nanotechnology can has an overall negative impact on the growth of nano firms in terms of employment. This is a hint to the fact that specialization is counterproductive for explorative, knowledge-intensive purpose in the GPT field under investigation here. Specialization suppresses multiple opportunities for nanotechnology as GPT to develop and inhibits possibilities of catalyzing effects and cross-fertilization. The differentiation into different subgroups emphasises that, however, this effect differs across different firm characteristics: The results for the independent variable of *LQ* are still significantly negative for high KIS and older firms (see Table 4: model IV and VII). These are the firms that are especially prone to exploitation activities, as they are knowledge-intensive. Hence, it might be the case that knowledge-intensive firms explore the nano field, as their flexibility of thinking might make it more easy for these firms to perceive possibilities of application of old nano knowledge in new fields. Another interesting issue is that *HQ* still shows statistically significant coefficients. In the case of all firms, SME and firms operating in knowledge-intensive sectors, we find significant coefficient with a positive sign. We interpret this as a statistical support for the fact that firms where knowledge is a crucial driver of employment growth strongly depend on highly qualified employees (as knowledge sources) in the region. The same is true for the independent variable of *R&D*.

As specialization suppresses exploration (e.g. Greve, 2007), this explains the negative influence of specialization on employment growth. Older firms already survived the critical start-up phase and, moreover, are more prone to possessing the necessary endowment with resources to further explore the field. For the other subsamples such as differentiation across *size* and *low KIS* or younger firms, no significant effect of specialization can be found. This is contrary to our expectation that especially young and small firm benefit from specialization, as they occupy mostly specialized niches when entering the market. This is why *H2a* cannot be confirmed by our results. To test *H2b*, we also included the squared form of *LQ* in the model. Our results suggest that too much specialization does not have any influence on the employment growth in firms active in nanotechnologies except for the case of low-KIS firms where too much specialization and too much anti-specialization, in contrast to moderate specialization is harmful. Although generally specialization of the regional knowledge base has no impact on a *low-KIS* firm's performance, employment growth declines when the region becomes too specialized. As this does only hold for one particular case, *H2b* cannot be confirmed here. This might be owing to the fact that specialization in general already is counterproductive to the firms' employment growth. This effect does not seem to become more serious with increasing specialization.

Summarizing, we hence state that regional specialization does have a mostly negative impact on nano firm employment growth, even though not for all firms similarly but depending on their knowledge-processing characteristics. As things stand, Hypotheses 2 can therefore be confirmed in general means. The results hence suggest that the average impact of specialization on employment growth (as discussed earlier in the text) appears to be related to average employment growth as well as to the year-to-year consideration of employment growth.

5.3 Robustness of the impact of specialization (Hypothesis 3)

In a last step, we analzse the robustness of the impact of specialization and the location characteristics on growth. We try to highlight the fact whether yearly changes of the level of specialization might interfere with yearly changes in the employment growth rates. This means, if growth in one year depends on an increasing level of specialization, the relationship between current employment growth and previous specialization might be a direct effect. To disentangle this dynamic effect, we conduct regressions where we include the different measures of specialization *LQ*, LQ^2, and the different *LOCATION* measures. Hence, we hypothesise that *specialization effects that are related to average employment growth are the same as those that are related to a year-to-year consideration of employment growth*. Table 5 presents the detailed regression results for the fixed effects model. Again, Table A3 clearly presents that *LQ* and LQ^2 ($r = -0.4078$) are correlated. We already stated in Hypothesis 1 that firms in nanotechnology are affected by location-specific characteristics (e.g. *HQ*, *INDDENS*, *IND*, *STUD*, and *R&D*). Thus, we neglect most of these indicators because in this analysis, it is beyond the scope to analyze the pure impact of location again. Now, we only consider the more particular impact of the level of specialization. The findings vary (see Table 5).

We start our discussion with a comparison between the firm characteristics that relate to average growth (H2) and the firm characteristics that relate to a year-to-year consideration (H3). As a result, if we change the perspective from average growth to a year-to-year consideration, we receive different results in the case of all subsamples. Obviously, the coefficients for *LQ* never become significant. First, if we look at the results for all firms together, we find no longer a negative coefficient for *LQ*. What we find is a significant negative coefficient for LQ^2 in the overall model I and the three subsamples of small firms (model II), high-KIS (model IV), and younger firms (model VI). We interpret this as a statistical support for the fact that employment growth tends to decline with very low and very high levels of specialization. Put differently, specialization hampers year-to-year employment growth of local firms if a certain threshold of specialization is undercut or exceeded. Also, in these cases, the effect of the average growth path is not confirmed for the year-to-year perspective. For the year-to-year consideration, our results suggest that specialization influences firm employment growth in a non-linear way (see Table 5). Although the marginal effect of specialization is initially insignificant, it becomes significant and negative for regions that exhibit extreme values of specialization. This means although generally specialization of the regional knowledge base has no impact on a firm's performance, employment growth declines when the region becomes too much or too less specialized. Even though there is no general positive effect for lower levels of specialization, this reminds us of an inverted u-shaped relationship between specialization and performance often found in empirical work on production (Betrán, 2011) stating that too much (or to less) specialization has a negative influence on performance.

Generally spoken, this model does not confirm the results of the OLS regressions (average growth) around Hypotheses 2. Hence, the results contradict what we expected in Hypothesis 3, which is why we have to reject it. The characteristics accompanying average growth are not usually related to occurrence of year-to-year employment growth. However, an analysis of the year-to-year growth process of nano firms provides additional information, as discussed earlier in the text. If we change the perspective from average growth to year-to-year consideration, the findings vary. Hence, the temporal structure of the growth process itself should be considered. And what is most important in terms of our initial questions: we never find a positive impact of specialization on the employment growth of nano firms. Referring to the prevailing of high tech of GPT features referring to the relevance of the surrounding, GPT features seem to outweigh high-tech ones—although further empirical investigation needs to be done to disentangle the concrete effects of specialization on firm growth in high—and nanotechnologies.

6. Conclusion

Nanotechnology firms' growth is influenced by the locations that host the firms. More particularly, we examined whether the local endowment with knowledge influences the growth of these firms. As we expected in view of nanotechnology firms operating on an innovation and hence knowledge intensive high technology field, the performance of these firms is—in general—stimulated by the local access to (high) knowledge. However, the actual impact of knowledge varies across firms with different characteristics. Although the share of highly qualified employees never hampers growth (although it seems not to advance it either in larger firms), the local stock of employees concerned with R&D has a hampering effect. We interpret this as a hint to the necessity of the knowledge to be marketable. However, this might also be interpreted as the inefficiency of knowledge transfer from universities to technology. Finally, knowledge is as relevant for nanotechnology firms as for other highly knowledge-intensive firms, regardless of the peculiarities a GPT implies: nanotechnology firms rely as much on knowledge spillovers as other high-tech (but not GPT) firms from other industries. The impact, however, depends on knowledge-processing characteristics like it is the case in other industries.

Moreover, the impact of knowledge for nano firm growth also depends on the characteristics of knowledge itself. We set out to investigate the special influence of specialization of the regional knowledge base. When analyzing average employment growth rates, the impact of specialization is counterproductive to some firms, it has no effect on growth in others. In the year-to-year consideration, however, regional specialization only has a negative effect in extreme situations. Although these results differ, it becomes clear that specialization does not have a positive effect on firm growth in nanotechnology. The relevance of these effects has, however, to be seen in context with the special characteristics of GPTs, which develop their positive and accelerating effect on growth in a setting that is open to exploration and cross-application (which is not supported by specialization). These findings point to the importance of our study: although it is popular among policymakers to support the establishment of specialized nano clusters, our results suggest that this regional specialization is not conducive for the firms. Moreover, it might even become a burden for the performance of some firms, depending on the local degree of specialization and the firm's knowledge-processing characteristics. However, our findings are relying on a small number of firms in nanotechnology only. Moreover, the indicators on the impact of local knowledge resources, such as *STUD* and *R&D* could be refined (e.g. disentangling relevant STUD and R&D, such as students in technological fields) to be able to further investigate *which* local knowledge is relevant. Further research should also be done on the effect of specialization in a larger sample or other (GPT) settings to confirm these results, especially in view of findings that state a positive effect of specialization for many other, but different circumstances and industries. It moreover lies beyond the scope of this article to investigate the mechanisms behind our findings. It would be interesting to learn how exactly local knowledge is processed, where spillovers indeed are effective, and how specialization exactly affects innovation in high technologies.

The conclusion of this article remains that local knowledge endowment positively influences firm growth in nanotechnology, whereas local knowledge specialization surely is not always positively affecting the growth of individual firms, pointing to the relevance of the GPT feature of nanotechnology for processing knowledge in firms.

Acknowledgements

The authors thank Dirk Dohse, two anonymous referees, and the participants of the DRUID Academy, 2012, in Cambridge for helpful comments, as well as the Karlsruhe House of Young Scientists and the German National Academic Foundation for financial support.

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Appendix

Table A1 Descriptive statistics

Variable	Observations	Mean (SD)	Min	Max
EMP	216	0.1398783 (0.4411129)	−3.610918	1.633717
KIS	216	0.8177966 (0.3868325)	0	1
SME	216	0.6313559 (0.4834625)	0	1
AGE	216	40.036199 (52.783163)	0	343
HQ	236	0.1150768 (0.0354213)	0.0472828	0.1844673
INDDENS	236	45.43375 (39.07808)	2.165327	165.8995
IND	235	10295.4 (12475.71)	13	70531
STUD	236	38148.5 (33889.06)	0	134260
R&D	236	9112.375 (11739.87)	140	39879
LQ	234	−5.342925 (58.55617)	−100	99.46871

Table A2 Time variation of each variable (panel dimension)

Variable	Mean (SD)	Min	Max	Observations
EMP				
Overall	4.7548 (3.2879)	0	12.9645	$N = 880$
Between	(3.3131)	0	12.9205	$n = 224$
Within	(0.1998)	2.1004	8.8239	T = 3.93
LQ				
Overall	−5.3078 (58.4519)	−100	99.5346	$N = 702$
Between	(58.3518)	−100	99.4997	$n = 234$
Within	(4.6276)	−30.2863	37.3654	T = 3
LQ^2				
Overall	3439.94 (3057.249)	0.7897	10,000	$N = 702$
Between	(3025.52)	13.3764	10,000	$n = 234$
Within	(468.0969)	−21.2303	5992.402	T = 3
INDDENS				
Overall	45.3757 (39.1297)	2.1295	167.8201	$N = 707$
Between	(39.308)	2.1729	165.6239	$n = 236$
Within	(0.8798)	41.6692	52.7028	T = 2.99
IND				
Overall	9760.35 (12534.96)	0	68,722	$N = 708$
Between	(12579.75)	0	68,096	$n = 236$
Within	(273.0092)	8373.681	11,276.35	T = 3

Table A3 Correlation matrix

	EMP	HQ	INDDENS	IND	STUD	R&D	LQ	LQ^2	SIZE	KIS	AGE
EMP	1.0000										
HQ	0.0573 (0.4020)	1.0000									
INDDENS	0.0482 (0.4809)	0.3720 (0.0000)	1.0000								
IND	−0.0343 (0.6160)	−0.0793 (0.2260)	−0.0584 (0.3726)	1.0000							
STUD	0.0165 (0.8092)	0.6294 (0.0000)	0.4509 (0.0000)	−0.0936 (0.1527)	1.0000						
R&D	−0.0509 (0.4567)	0.5931 (0.0000)	0.0989 (0.1299)	0.0069 (0.9162)	0.2374 (0.0002)	1.0000					
LQ	−0.1074 (0.1164)	0.2296 (0.0004)	0.0195 (0.7670)	−0.0005 (0.9945)	0.1924 (0.0031)	0.2309 (0.0004)	1.0000				
LQ^2	−0.0214 (0.7552)	−0.1158 (0.0770)	−0.0186 (0.7777)	−0.0794 (0.2261)	0.0389 (0.5542)	−0.0541 (0.4098)	−0.4078 (0.0000)	1.0000			
SIZE	0.1632 (0.0163)	−0.1130 (0.0832)	−0.1324 (0.0422)	−0.0183 (0.7802)	−0.1192 (0.0676)	−0.1142 (0.0800)	−0.0656 (0.3174)	−0.0599 (0.3620)	1.0000		
KIS	0.1624 (..0172)	0.1646 (0.0117)	0.0169 (0.7973)	−0.0054 (0.9347)	−0.0054 (0.9347)	0.2196 (0.0007)	0.0638 (0.3308)	0.1095 (0.0946)	0.1457 (0.0258)	1.0000	
AGE	−0.1922 (0.0056)	−0.0240 (0.7224)	−0.0560 (0.4065)	0.0666 (0.3245)	0.0142 (0.8339)	0.0481 (0.4760)	0.0497 (0.4633)	0.0289 (0.6700)	−0.1420 (0.0353)	0.0055 (0.9333)	1.0000

Table A4 VIF test for multicollinearity

Variable	VIF	1/VIF
HQ	3.51	0.2850
INDDENS	1.31	0.7661
IND	1.63	0.6125
STUD	1.83	0.5458
R&D	3.42	0.2921
LQ	1.29	0.7750
Mean	2.17	