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Impact of Local Knowledge Endowment on Employment Growth in Nanotechnology

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Abstract

Despite the fact that most of the previous studies that examine firm growth fairly ignored the possible importance of local aspects for firm growth, there is a large body of literature that suggests that there are reasons to expect location being relevant for firm growth. Merging the main theoretical considerations of the Endogenous Growth Theory, coined by Romer (1986, 1990) and Lucas (1988) and New Economic Geography, brought up 1991 by Krugman, the seminal work of Glaeser et al. (1992) pointed to the role of knowledge and its external effects ? knowledge spillovers - for the growth of cities. Knowledge, the most important input to innovation and hence economic growth, generates externalities due to its non-rival and non-excludable nature thereby improving the efficiency of innovations. These externalities, however, are spatially bound. It is hence natural to assume that regions that are well endowed with knowledge capital are conducive to innovative activity. Advancing this idea, the expectation that firms with a high share of innovative activity benefit from this characteristic of location in term of higher profitability and better performance is quite natural.

However, the aspect of the local endowment with knowledge as determinant of firm growth has only been considered recently (e.g. Hoogstra and van Dijk 2004, Audretsch and Dohse 2007). Moreover, and more particularly, it is especially worth investigating the influence of the characteristics of the local knowledge base. One of these characteristics, the extent of specialisation, has become very popular in the last decades by means of a policy measure: The development and support of ?regional technology clusters? has been widely implemented to attract high performing high-tech firms. Specialised knowledge shall produce inter-industry spillovers and thereby support the efficiency of firms in the cluster and trigger regional economic growth. In the context of local determinants of firm growth it has hence to be investigated whether this local knowledge specialisation is indeed a driving factor of firm growth.

Since these questions seem to be especially interesting in the context of highly knowledge dependent and growth promising general purpose technologies we investigate the performance of German firms in nanotechnologies. Taking firms engaged in a general purpose technology (GPT) as object of study implies an additional tension: Since GPTs are growth promising because of their generality of purpose (as their name proposes) the role of specialisation for GPT firms? growth might be particularly ambiguous and interesting.

This paper investigates the contribution of location-specific characteristics (e.g. regions share of high qualified employees) and knowledge endowment (e.g. specialization) to firm growth in nanotechnology. We exploit a panel of 187 German firms covering the time period from 2007 to 2010. Our empirical analyses apply two regression techniques, a simple OLS regression (average growth) and fixed effects model (yearly growth rates).

Our findings suggest that location-specific characteristics and knowledge specialisation do directly impact firm growth in nanotechnology. Our findings show, on average, that the impact of these variables differs entirely across firm size classes, knowledge intensive sectors and firm age. Especially regions that offer higher share of qualified employees can stimulate firm growth in smaller firms. In particular, being embedded into regions with higher level of specialisation is more conducive for firms that belong to a particularly knowledge intensive sector and for younger firms that are primarily engaged in nanotechnology. Finally, the impact of specialisation on firm growth in nanotechnology firms in the long-run is consistent with the short-run consideration.

Jelcodes:O31,O32

Impact of Local Knowledge Endowment on Employment Growth in Nanotechnology

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Abstract

This paper investigates the contribution of location-specific characteristics and local knowledge endowment to employment growth in nanotechnology firms. We exploit an unbalanced panel of 216 German nanotechnology firms covering the time period from 2007 to 2010. The empirical analyses apply two regression techniques, a simple OLS regression and fixed effects model. Our findings suggest that location-specific characteristics and local knowledge specialization do directly impact employment growth in nanotechnology. Our findings show, for average growth, that regions that offer high share of qualified employees can stimulate employment growth in smaller and younger firms. In contrast, being embedded into regions with high level of specialization is counterproductive for older firms and firms that belongs to a particularly knowledge intensive industry. If we change the perspective from average growth to a year-to-year consideration the findings vary. Put differently, a higher degree of specialization hampers year-to-year employment growth in different subsamples.

Key words: Employment growth, local knowledge endowment, general purpose technology, specialization, nanotechnology, spillover

JEL codes: D83, O31, R11

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1. Introduction

All over the world nanotechnology are seen as the most promising future technology with great economic potential for employment and growth. The term nanotechnology thereby refers to most different types of analysis and processing of materials which have one thing in common: Their small size (1-100nm). 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 shape. It is widely accepted as being the next general purpose technology and accordingly its economic impact might be compared e.g. to the steam engine, electricity or ICT.

Nanotechnology is still a young and dynamic technology and innovation activities are essential firm activities. Due to fragmented research, development and production processes, firms usually only provide parts of complex value creation processes. They are thus embedded in various networks and it is reasonable to assume that the characteristics of the economic surrounding feeds back to nanotechnology firm's performance.

This paper addresses the impact of two economic key characteristics of nanotechnology in order to assess the technology's potential to fulfil the enormous expectations its 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 nanotechnologies. Aside from the firm-specific characteristics, location-specific properties such as specialized environment become apparent. Firms' specialized environment might accounts for growth relevant knowledge spillovers that in turn may create productivity gains. Key determinants are thereby a sufficient and well connected overlap to other actors (i.e. absorptive capacity) and the availability of qualified labor. Following this reasoning, the actor's regional, anchorage and especially the composition of regional labor markets play a crucial role.

In contrast to this is the *general purpose character* of nanotechnologies allowing the technology to be used and placed almost anywhere. Thus, it is not regional embeddedness *per se* that positively contributes to employment and growth, but in contrast: Too much local specialization might inhibit the technology's use in a multitude of application field, thereby possibly suppressing potential opportunities for cross-fertilization and innovation-enhancing feed-back mechanisms across divers and so far unrelated value creation chains.

Thus, tying in with already existing regional specialization is neither necessary nor per se conducive for a successful technology development. Consequently, in which economic surrounding nanotechnology firms actually realize their economics potential and hence to what extent they finally contribute to the expected goal of job creation and growth is not pre-determined. It is reasonable to assume that aside from firm-specific characteristics also location-specific attributes impact on the result. Less clear is to disentangle the impact of various influencing factors.

This is the staring point of the paper 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 in firms? (ii) What is the impact of regional specialization, or put differently which characteristic of nanotechnology predominates: its character as high technology (i.e. being located in sufficiently specialized region) or the character as a general purpose technology (according to which opportunities aside from already existing specialization may be even more important).

The remainder of this paper is structured as follows: In Section 2 we supply the theoretical background and derive our main hypotheses. Section 3 introduces our methodology and data and shows the stochastic properties of the sample. In section 4 we present our results and interpretations and section 5 briefly concludes.

2 Theoretical background and hypotheses

There are a wide range of theories and empirical approaches dealing with firm growth (for an overview see, e.g., Coad 2007). The existing research on determinants of firm growth has focused on several factors, such as characteristics of the entrepreneur (e.g., education), characteristics of the firm (e.g., location, firm size, firm age, industry affiliation) and strategy of the firm (e.g., external equity) (Storey 1994). Empirical findings are concerned with topics such as the identification and analysis of firm growth stages or firms' development paths (e.g., Delmar et al. 2003), Gibrat's Law[1] (e.g., Bottazzi and Secchi 2006), or with the detection of firm, sector and industry affecting firm growth (e.g., Harhoff et al. 1998). Related theories address the topic from very different perspectives ranging from neoclassical theories of optimal size (Coase 1937), Penrose's theory focussing on the internal learning-by-doing processes (Penrose 1959), to evolutionary concepts in which the fitness of firms plays a central role (e.g., Coad 2007) and the socio-economic view in which the available resources and the competition for these resources are the core concepts (e.g., Uhlaner et al. 2007). We will address some of these empirical studies in this paper.

A bulk of studies investigates the impact of innovation activities (e.g., R&D expenditure, product and process innovation) on firm growth. Del Monte and Papagni (2003) show that the growth rates of firms are positively correlated with the research intensity. In line with this, Adamou and Sasidharan (2007) study the impact of R&D by using panel data on Indian manufacturing firms. They argue that R&D is an essential determinant of firm performance. Furthermore, they find that an increase in R&D induces higher growth. The availability of human capital, especially skilled workforce or qualified employees (i.e. incorporated knowledge) is therefore linked to the success of an innovating firm's performance. The lack of human resources and difficulties in getting qualified employees negatively affects the growth of firms (e.g., Acs and Audretsch 1990, López-Garcia and Puente 2009). This constant need of knowledge resources of innovating firms suggests the special relevance of location: Feldman (1994) suggests that especially innovative activity clusters spatially. One of the reasons is the possibility of knowledge spillovers. Because knowledge is of non-excludable non-rival nature, private production of knowledge increases the stock of knowledge available to anyone, increasing the efficiency of their knowledge activities (Feldman and Kogler 2010). Hence from a technological point of view, spillovers constitute a positive externality, while there might be negative economic effects concerning competition and incentives to innovate (Jaffe 1986). However, spillover opportunities decrease with distance, as knowledge that is highly contextual most frequently requires interaction and face-to-face contact in order to spill over (von Hippel 1994). Innovating firms are not isolated, self-sustained entities but rather highly linked to their environment (Fritsch and Slavtchev 2010). 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 the characteristics of location seem to preserve and even reinforce an innovating firm's growth process. However, until recently little effort has been done to analyse 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 has only been studied recently (e.g. Gabe and Kraybill 2002, Audretsch and Dohse 2007, Weterings and Boschma 2009). Following Audretsch and Dohse (2007, p. 100), who find that regions abundant in

[1] Gibrat's law states that firm growth is essentially random. Being on of the first contributions on firm growth, Gibrat's law is considered falsified by most researchers nowadays.

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:

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. While a cluster always refers to a specialised 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) defines cluster as "geographically proximate group of inter-connected companies and associated institutions in a particular field that is linked by commonalities and complementarities"[2]. As a positive external knowledge spillover they increase their productivity and economic performance. There is, indeed, 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. 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 will therefore extend from the basic question of the impact of local knowledge endowment to the more particular issue of the composition of this knowledge and ask whether it is indeed specialised knowledge that supports firm growth.

2.1 Determinants of firm growth in nanotechnology

Nanotechnology is often seen as future key technology. It is interdisciplinary and combines a lot of classical basis technologies. It encompasses the targeted manipulation of material and structures sized less than 100 nanometres in order to give the material size-specific properties and functionalities (Youtie et al. 2008). The application of nanotechnology is possible in virtually every field of the economy. It is expected that diverse applications bring about new effects in larger structures of which nanotechnologies become part and therefore allow for the improvement of old or the development of new products. Nanotechnology is seen as substantial contributor to innovativeness, economic growth and employment (Bozeman et al. 2007). For its *wide variety of uses,* the inherent *technological dynamism* and *innovation spawning* nanotechnology is systematically described as general purpose technology (GPT). This term was coined by Bresnahan and Trajtenberg (1995), pointing to a GPT's potential to induce a great many innovations, thereby advancing the technological development and hence to act as engines of growth in the coming decades. In this respect it is particularly interesting how firms dealing with nanotechnology can realise this potential and hence benefit from nanotechnologies as engines of growth and translate this into own firm growth. When dealing

[2] Porter (2000): p. 254

with the determinants of firms in nanotechnology and their growth, several particular issues should be taken into account.

First, as GPTs in general and nanotechnology in particular entail a great variety of innovations, it is reasonable to assume that firms in these industries locate in regions where a wide basis of knowledge increases the probability of knowledge creation and knowledge spillovers (Grimpe and Patuelli 2010). The location of nanotechnology's industries, i.e. the proximity of nano-firms to other knowledge producing entities, is thus assumed to play an important role to the efficiency of their innovative activity and hence their performance.

Second, based on the GPT and interdisciplinary nanotechnology definition and its infancy stage, it can be derived that firms dealing with nanotechnology differ in their characteristics, i.e. that they are distributed across industries, firm size classes and age (see e.g. Schnorr-Bäker 2009). The empirical literature reveals main findings of firms such as firms in nanotechnology related to sectoral and industry specificities, as well as firm age and firm size. For an example take Davidsson and Delmar (2003), who point out that high-growth firms are overrepresented in growing industries with a large inflow of new and small firms, especially in knowledge intensive industries. However, due to nanotechnology's GPT character, existing and older firms would also apply nanotechnologies. Hence, size, age and industry affiliation might be an important factor to disentangle when examining firm growth.

Third, within an agglomeration, it has intensively been argued that clustering of firms in the same industry, and hence specialization of the region, opens opportunities for inter-industry knowledge spillover. Particularly inter-industry knowledge spillovers have recently been the basic rationale for regional cluster policies supporting regional specialization with the aim of a better and faster development of high-technologies, among them nanotechnology. However, particularly within the context of GPTs, the effect of regional specialization on firm performance has to be investigated cautiously. While some kind of specialised knowledge is needed in order to achieve sufficient expertise for leading-edge innovations at the technological threshold of any high-technology (Garcia-Vega 2006, Leten et al. 2007), or, put differently, to advance and complement existing knowledge incrementally, specialization at the same time inhibits the growth-promising effects of the GPT. These are based on the multitude of potential application fields which induce continuous technological improvements, thereby setting innovation incentives and provoking a feed-back mechanism along the value creation chains. By exploring the field and using the same (existing) knowledge in different fields, the productivity of innovations can be improved and opportunities of cross-fertilization can be opened. For this scope, however, specialization seems rather counterproductive. It is hence important to investigate whether and to which extent regional specialization is conducive to the performance of firms – particularly in the field of nanotechnology as GPT.

2.2 Expectations for the determinants of firm growth in nanotechnologies

Following the argumentation above, we propose the natural expectation that location does affect the growth of firms in nanotechnologies. We moreover assume that employment growth in nanotechnology firms is strongly related to successful innovative activity irrespective of which particular kind. Technological change and innovation are widely seen as the key for economic growth. We therefore apply this relationship to the context of the individual firm. Following Feldman (1994), knowledge spillovers are especially relevant for small firms since the resources necessary in order to maintain the knowledge base are typically beyond their means. This suggests that the extent to which external knowledge is crucial and can be absorbed differs widely across different firm size classes and knowledge intensive sectors. Paying attention to the characteristics of the structure of the region a firm is located in and the knowledge processing characteristics of the firm itself, we hypothesize that:

H1: Location characteristics do stimulate the employment growth of firms in nanotechnologies.

H1a: The importance of the characteristics differs across firm size classes, knowledge intensive sectors and age groups. In particular 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.

H1b: A high share of R&D employees in the region negatively influences employment growth. Actually, firms where knowledge is not a crucial driver of employment growth depend less on other R&D knowledge sources in the region.

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 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 since 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. Catalysing knowledge recombination and fertilising 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). Specialization is necessary to develop sufficiently strong capabilities in particular domains in order to be able to realize economies of scale in technology development while incrementally advancing the technology. Hence, specialization might have a positive effect on growth in nano-firms: Firms that are not particularly intensive in knowledge, or put differently do not rely as much on knowledge as other do 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 due to the fact that small firms are often highly specialised and enter the market via specialised niches (van der Panne 2004). Since 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.

H2: Local specialization impacts the employment growth of firms in nanotechnology negatively.

H2a: While specialization has a negative impact on employment growth in knowledge intensive firms, it has a positive impact on smaller and younger firms.

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.

H2b: Irrespective to the characteristics of a firm, too much local specialization has a negative impact on employment growth of firms in nanotechnology.

Finally, we analyse the robustness of the impact of specialization 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 the impact of specialization on average employment growth of firms in nanotechnology is consistent with yearly growth rates of these firms, or, put differently

H3: The impact of specialization on employment growth in nanotechnology firms is robust across a year-to-year consideration.

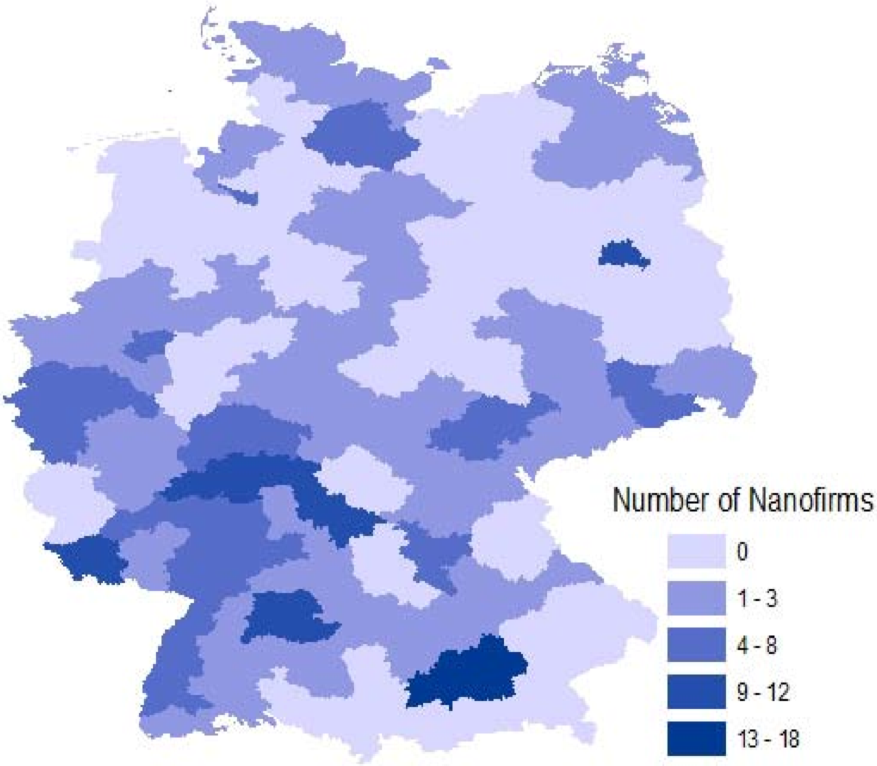
The expected results will sharpen our understanding of the association between concentrated activity of firms and the corresponding performance in the field of nanotechnologies as an emerging GPT. They may serve as a starting point for regional policy aiming at the improvement of the regional factors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

3 Methodology and Data

3.1 Data source

In our unique data set, we focus on firms operating in fields that apply nanotechnology, 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 those firms are intensive in innovation - which is by definition extraordinarily knowledge intensive. 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 since nanotechnology as GPT do not constitute a single industry, but are – at least potentially – present in a wide range of different industries. 216 of 1950 contacted firms answered, which gives a response rate of 11.1 percent. To ensure whether our firm sample is representative of the entire population, we run a t-test for the two groups of interest. The independent samples t-test compares the difference in the means from the two groups to a given value (usually 0). In other words, it tests whether the difference in the means is 0. In this vain, we split our firm sample into two groups: (i) response at an early stage and (ii) response at a later time. In doing so, we compare the two groups in regard to their number of employees and profits. Thereby, group (ii) stands for the firms that will never provide a response (i.e. non-response problem). In the case of the number of employees, the t-statistic is 1.1866. The corresponding two-tailed p-value is 0.2371, which is greater than 0.05 (i.e. non-significant). We therefore conclude that the mean difference of the two cohorts is not different from 0. In the case of profits, the t-statistic is -0.9374 and p-value is 0.3499, which is also greater than 0.05 (i.e. non-significant). 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, which might lead us to the fact that our firm sample is representative to the entire population.

Figure 1: Distribution of Answering Nano-Firms across Germany



The level of analysis within our survey is the geographical level of planning regions ('Raumordnungsregionen' (ROR)). 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 (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: Out of the 97 planning regions, the nanotechnology firms in our sample are located in 62 different regions[3]. Figure 1 displays this distribution: While in some regions no nanotechnology firms are located, there are regions hosting a multitude of nanotechnology firms.

3.2 Dependent variable

Before starting with the regressions, an operationalisation of the term firm growth is necessary. There is a wide range of definitions that deal with firm growth. Some definitions are based on the number of employees (e.g. Hölzl and Friesenbichler 2008) whereas others are based on sales and turnover (e.g. Daunfeldt et al. 2010). Garnsey et al. (2006) suggest that

[3] 62 different regions (ROR): avg.: 3.8 max: 18 and min: 1

"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)"[4]. In our analyses, we use the growth measure of the number of employees (i.e. employment growth). For the regression model we employ the relative growth indicator. In this paper we 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 2007). The year of the financial crisis, 2008, was replaced by the mean value because the stochastic properties of the growth rates exhibit a significant different behaviour and thus they qualify themselves for being a research topic on their own. Furthermore, an appropriate replacement of the missing values is a neighbouring nonmissing value (i.e. [_n-1] or [_n+1])[5] for each individual firm in the panel. Nevertheless, in some cases number of employees is completely missing for all years. Hence, we are not able to replace these missing values.

3.3 Explanatory variables

Regarding our hypotheses, we employ several independent variables. These variables display firm-specific characteristics and location-specific characteristics. The firm-specific variables reflect rather usual factors found to influence employment growth, such as e.g. firm size, age and industry affiliation. Location-specific variables by contrast shall reflect the knowledge characteristics that are specific to the environment, i.e. to the region or more particular the industry in the region 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-specificity

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 (see e.g. Audretsch 1998). We hence assume small and medium-sized firms (*SIZE* = 1) to benefit different 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*) or not (*KIS*=0, *low-KIS*).[6] *KIS* is constructed by the share of 'knowledge workers' in an industry's labour 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 in order 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

4 Garnsey et.al. (2006): p. 11

5 by id (year), sort: replace employees = employees_n-1] if employees >= . / by id (year), sort: replace employees= employees[_n+1] if employees >= .

6 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.

(e.g. Coad 2010). We therefore include *AGE* (i.e. year since foundation) as control variable to improve the fit of our estimations. Moreover, since 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.

(2) Location-specificity 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 *IND* variable, by contrast, displays employment in the firms' industry. 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).[7] Hence, firms residential in regions endowed with high level of human capital are assumed to have easy and better access to knowledge which subsequently increases productivity and growth (Audretsch and Dohse 2007). 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 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 catch-all region-specific variable that is not directly related to knowledge spillover aspects: *INDDENS* is constructed by measuring industry density and hence catches effects of agglomeration that refer to firm clustering in general. It is therefore employed to improve model fit. 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). This does not only happen through research results open to the public and ready to be exploited as knowledge spillovers, but also as universities educate and train the individuals in which the relevant knowledge is (will be) incorporated, thereby increasing the region's pool of individuals with high levels of absorptive capacities. In order to be able to distinguish between the different impacts of university research, we employ the number of students *STUD* instead of a more standard university dummy as it also accounts for size and impact of the university in a region. Following the argumentation above, we expect knowledge spillovers to increase with available knowledge resources and hence the *STUD* should have a positive impact on firm growth. A similar argumentation holds for *R&D,* a variable displaying the share 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 very likely to be another source of knowledge spillovers that are effective within a particular region and moreover represents the propensity of a region to be innovative. The specialization *(LQ)* variable measures region-specific knowledge-resources and refers to the characteristics of the knowledge within a region. It is constructed using employment data. Specialization corresponds to the industry in which the firm operates. LQ is calculated by the ratio of the share of employees of a region in this industry, divided by the total share of employees in this very field in the whole country:

[7] 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).

LQ indices are usual measures for specialization externalities (Paci and Usai 1999). For the empirical analysis we employ a standardisation, making the index symmetric and easier to interpret by using the formula $LQ=100*$ $(LQ^2 - 1)/(LQ^2 + 1)$, which constrains possible values within the interval (−100,100). 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).

Table 1: Description of explanatory variables

Category	Variable	Description	Nature
Firms-specific characteristics	*SIZE*	Small and medium enterprises. Firms classified as small and medium-sized enterprises are defined as those with less than 251 employees (SME=1).	subsamples and control variable
	KIS	Knowledge intensive sectors. Indicates whether a firm belongs to a particularly knowledge intensive sector within the sample: Firms in sectors with an above-average share of employees with university degree are knowledge intensive (KIS=1).	subsample and control variable
	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.	subsamples and control variable
Location- specific characteristics	*HQ*	Region exhibits a share of highly qualified employees with university degree in the top quartile.	independent variable
	INDDENS	Measures industry density (employees in industry per km²) in a region, catchall variable for agglomeration effects.	independent variable
	IND	Absolute employment in the firms' industry, pointing to the actual strength of the firm's industry in the considered region.	independent variable
	STUD	Absolute number of students in the considered region.	independent variable
	R&D	Absolute number of employees in R&D in the considered region.	independent variable
	LQ	Normalized Revealed Technological Advantage, i.e. relative specialization in the firm's industry and region compared to other regions.	independent variable

3.4 Descriptive statistics and stochastic properties

The final database consists of 216 firms. The descriptive statistics for the employed variables are given in Table 2.

Table 2: Descriptive statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
EMPL	216	0.1398783	0.4411129	-3.610918	1.633717
SIZE	216	0.6313559	0.4834625	0	1
KIS	216	0.8177966	0.3868325	0	1
AGE	216	3.000362	1.200884	0	5.83773
HQ	216	0.1150768	0.0354213	0.0472828	0.1844673
INDDENS	216	45.43375	39.07808	2.165327	165.8995
IND	216	8001.506	34290.28	1	437500
STUD	216	38148.5	33889.06	0	134260.4
R&D	216	9112.375	11739.87	140.1972	39878.7
LQ	216	-6.953736	58.34249	-100	99.47198

We are aware of the fact that our nano firm sample is characterised by different stochastic properties. Therefore, we analyse the distribution of employment growth rates to show the importance of the distinction between different subsamples. Table 3 pictures the distribution of growth rates within different subsamples, where *m*, stands for the mean and trend of the data, *a* for the scale parameter and the shape parameter *b*. The shape parameter *b* is the crucial one for our analyses, because it gives information about the fatness of the tails. This means the larger b, the thinner are the tails (i.e. if *b* decreases the tails of the density become fatter). Hence, if b = 1 the distribution reduces to a Laplace, whereas for b = 2 we recover a Gaussian distribution. In our case, the parameter *b* gets smaller with increasing firm size. Estimates for smaller and medium-sized firms (SME) indicate that employment growth rates seem not really to distribute according to a Laplace: the shape parameter *b* is equal to .728 (SME), not very close to the theoretical Laplace value of one, the Gaussian value of two or the Subbotin super Laplace tails of 0.5. In our case, (super-) Laplace distribution is a better fit for larger firms (e.g. Fu et al. 2005) whereas the shape parameter is equal to 0.5 (0.446). Furthermore, the scale parameter *a* decreases with increasing size that also goes in line with the common literature (e.g., Bottazzi et al. 2011) on firm growth. This means larger firms display lower variability in their growth dynamics. In this vain, the distinction between different firm size classes provides important information on the growth process itself. As a next step, we distinguish between high-KIS and low-KIS firms. In the case of low-KIS, the parameter *b* is equal to 1.468, hence, not very close to the theoretical Laplace value of 1, the Gaussian value of 2 or the Subbotin super Laplace tails of 0.5. If we look at the results for high-KIS firms we receive a completely different shape parameter *b*. Hence, and as you already know if *b* is equal to 1 the distribution reduces to a Laplace. In our case, the shape parameter is not very close to Laplace.

Table 3: Distribution of employment growth rates

Parameter		all firms	SME	large firms	high-KIS	low-KIS
b	Par.	.823	.728	.446	.770	1.468
	Std.err.	.099	.088	.083	.101	.485
a	Par.	.239	.248	.116	.244	.216
	Std.err.	.021	.024	.022	.025	.040
m	Par.	.110	.154	.00009	.106	.148
	Std.err.	.013	.012	.000	.014	.037

In respect to the distribution of growth rates, the variables KIS, SIZE, AGE[8] are hence used to distinguish between the different subsamples. Table 3 shows the number of firms differentiated by different firm size classes. Firms classified as small and medium-sized enterprises are defined as those with less than 251 employees (European Commission 2003). Table 4 shows the share of firms differentiated by various firm-specific knowledge processing characteristics such as *KIS*[9] (i.e. the most knowledge intensive sectors) and *AGE* (i.e. younger and older firms) in the time period from 2007 to 2010. Table 3 shows that in our sample small and medium-sized firms are overrepresented. However, this is in line with the overall distribution of firms across size regardless of their technological background: SMEs are always overrepresented. More particularly, nano-firms are mostly SMEs and more seldom larger firms (Schnorr-Bäcker 2009), which is why our sample represents the population well Additionally, Table 3 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. Hence we separate our sample into firms that are younger than the modal age of eight years and firms that are older than the modal age of eight years (e.g., Fagiolo and Luzzi 2006, Huergo and Jaumandreu 2004b,a). Estimates for younger firms indicate that employment growth rates seem to distribute according to Laplace: the shape parameter *b* is equal to *b* = 1.075 very close to the theoretical Laplace value of 1. In contrast, *b* gets smaller with increasing firm age (i.e. *b* = .766). In this vain, the distinction between different age groups (i.e. younger and older firms) provides additional information on the growth process.

Table 4: Firm-specific characteristics

Category	Subsample	Description	Frequency	Percentage
SIZE	SME	1≤ x ≤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 a paper by Audretsch and Dohse (2007): pp. 89
** Cut-off point in terms of younger/older firms: 8 years since foundation (e.g., Coad 2010)

3.5 Regression approach and model fit

First, we set up a regression approach with a linear model (see Equation 1 and 2) to analyse the average growth of firm. As independent variables all the described variables are used. We use the standard regression approaches since 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

[8] A majority of previous research tends to emphasize that younger firms exhibit higher growth rates than their larger counterparts (Jovanovic, 1982). 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. Most studies show that firm growth decreases with firm age (e.g., Acs and Mueller 2008, Coad 2010).
[9] The firms in our sample operate on 10 different nanotechnology fields: avg.: 2.1 max: 7 and min: 1

whether firm growth in nanotechnologies' is affected by different location-specific characteristics. Again, we analyse the average growth effect of these independent variables. First, we primarily investigate the impact of indicators on the average growth (from 2007 to 2010) of employment. In our equation, *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:

6log + 7log + 8 +

However, in equation (1) only location-specific (i.e. regionally determined) characteristics are considered and the degree of specialization of the local knowledge base is still neglected. Since we assume that regional specialization has an influence on nano-firm, we employ the *LQ* measure as well as its squared term LQ^2. Again, *LOCATION* stands for the various kinds of location measures, represented by *HQ*, *INDDENS*, *IND*, *STUD* and *R&D* to fit our model. For the overall model we also control for *SIZE, KIS* and *AGE* of the nano-firm. Thus, we investigate the impact of indicators on the average growth (from 2007 to 2010) of employment:

Third, we analyse 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. As recently described, we investigate whether the yearly changes of the level of specialization might interfere with the yearly changes in the employment growth rates. This means, if growth in one 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. To disentangle this dynamic effect we conduct a cross-sectional time series model. Additionally, we are no longer interested in average growth (equation 1 and 2) but in year- to-year growth. 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. 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 (i.e. Prob>chi2 = significant). Furthermore, we conduct one regression set for all firms together and then two other regressions for each firm *SIZE*, *KIS* and the *AGE* groups separately. Hence, our equation 3 follows as:

Finally, we test and control for multicollinearity (see appendix correlation matrix in Table A1) and endogeneity. Moreover, we use the first year value in 2007 (or the first available value) of observation as independent variables (i.e. *HQ, INDDENS, IND, STUD, R&D)* 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.

4 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 Table 5 - 7.

4.1 Location characteristics (Hypotheses 1)

As we want to especially gain information on the location characteristics that contribute to the growth of firm's active in nanotechnology, we differentiate between the characteristics of the structure of the region a firm is located in. We assume that *location characteristics do stimulate the employment growth of nano-firms (H1).* Furthermore *the importance of the characteristics differs across SIZE, KIS and AGE (H1a). Additionally, a high share of R&D employees in the region negatively influences employment growth. Actually, firms where knowledge is not a crucial driver of employment growth depend less on other R&D knowledge sources (H1b).* The results for the regression analysis are presented in Table 5. In our analysis we use the following location-specific characteristics (as described in section 3.3): *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.

Table 5: OLS - employment growth (EMP)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	All firms	SME	Large firms	KIS=1	KIS=0	younger	older
Variables	EMP	EMP	EMP	EMP	EMP	EMP	EMP
HQ	0.740*	0.625*	0.103	1.165*	-1.807	4.946*	0.0566
	(0.922)	(1.391)	(1.018)	(1.079)	(1.266)	(2.849)	(0.955)
INDDENS	0.000759	0.00130	-0.000773	0.000680	0.000786	0.000640	0.000479
	(0.000857)	(0.00141)	(0.000858)	(0.00107)	(0.000937)	(0.00254)	(0.000913)
IND	-3.15e-07	-9.31e-08	-5.38e-07	-2.78e-07	-1.59e-05**	-9.64e-06	-2.25e-07
	(8.48e-07)	(1.15e-06)	(1.09e-06)	(9.12e-07)	(1.15e-05)	(2.42e-05)	(8.10e-07)
STUD	1.57e-07	-6.88e-08	-4.59e-07	3.91e-07	-2.51e-06**	1.50e-06	-1.89e-07
	(1.05e-06)	(1.59e-06)	(1.15e-06)	(1.22e-06)	(1.91e-06)	(3.38e-06)	(1.09e-06)
R&D	-0.00158	-0.00329	-0.000831	-0.00136	-0.00280*	-0.000800	-0.00211
	(0.00278)	(0.00406)	(0.00317)	(0.00323)	(0.00409)	(0.00771)	(0.00297)
SIZE	0.153**			0.148*	0.162*	0.228	0.102
	(0.0638)			(0.0755)	(0.0872)	(0.268)	(0.0666)
KIS	0.0121	-0.00628	0.0248			0.0364	0.0162
	(0.0814)	(0.122)	(0.0961)			(0.214)	(0.0897)
AGE	-0.0701***	-0.0844	-0.0197	-0.0702**	-0.0706***		
	(0.0263)	(0.0563)	(0.0325)	(0.0324)	(0.0231)		
Constant	0.0155	0.408**	0.194	0.0213	0.138**	0.0181	0.0457
	(0.101)	(0.194)	(0.179)	(0.0920)	(0.117)	(0.344)	(0.108)
Obs.	216	144	72	178	38	42	174
R-squared	0.033	0.038	0.033	0.028	0.216	0.051	0.021

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the first step, we find significantly negative coefficients for the *AGE* of firms. This especially holds for the subsamples of all firms, smaller firms and both subsamples of KIS. This means that older firms are less likely to show higher growth, while younger firms are more likely to show higher growth in terms of employment growth. This also goes in line with the findings of many other scholars before (e.g., Audretsch and Dohse 2007). 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 (see Coad 2006). Furthermore, we find a positive effect of *SIZE* for both knowledge classes and older firms. The positive coefficients suggest that employment growth tends to increase as the firm becomes larger.

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 points 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, knowledge intensive industries 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 due 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 since they benefit from internal economies of scale in knowledge production just because their own knowledge stock is larger. Looking at the results of firms that belong to a knowledge intensive industry (i.e. *KIS*=1; above average of share of knowledge workers), we also find a strong positively significant coefficient. This means, firms with high knowledge intensity experience higher employment growth in regions with access to highly qualified employees which is very intuitive as these firms are highly knowledge intensive in their activities. Otherwise and in the case of low-knowledge industry (*KIS=0*) the coefficient shows no longer a significance. This seems similarly plausible since 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* the estimation of 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 (older than 8 years). This suggests that younger firms experience higher employment growth if they have access to qualified knowledge workers in their region where there are located in. 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 to the nanotechnology-market and its relevance for success in the beginning phase where concepts are developed and 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, which might indeed 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 common share of R&D employees in the region. For most of the models we receive a significant coefficient with a negative sign. This result especially holds for the models V (*Low-KIS*). This is a very interesting issue. The negative and statistically significant coefficients of *R&D* indicate that employment growth tends to decline with a high share of R&D employees in the region. This especially holds for *Low-KIS*. While 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 and labor. The kind of R&D processed might e.g. be too basic or to incoherent to be beneficial for firms that are interested in commercialization. For instance, Frenken et al. (2007) and 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. Actually, we are able to entirely confirm our assumption H1b.

To sum up, our expectations (hypotheses 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 and it differs. We obtain the result that the impact of highly qualified employees (*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 hence 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 (e.g., 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, this confirms the natural expectation, that 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.

4.2 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. Since 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 *local specialization impacts the employment growth of firms in nanotechnology negatively*, the extent of which we restrict in *H2a to being positively influent on employment growth in small and young firms.* We moreover assume a non-linear impact of *LQ* as *H2b* states that *irrespective to the characteristics of a firm, too much specialization has a negative impact on employment growth of firms in nanotechnology.* As you can see in Table 6, the independent variable of interest is *LQ*, representing the extent of regional specialization. Moreover, we also included *LQ²* in order 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*) as well as age groups (*AGE*).

Table 6: OLS with LQ-variables - employment growth (EMP)

Variables	(I) All firms EMP	(II) SME EMP	(III) Large firms EMP	(IV) KIS=1 EMP	(V) KIS=0 EMP	(VI) younger EMP	(VII) older EMP
LQ	-0.00101*	-0.000738	-0.000923	-0.00126*	-0.000408	-0.000788	-0.00121**
	(0.000572)	(0.000858)	(0.000630)	(0.000684)	(0.000955)	(0.00171)	(0.000602)
LQ²	-8.99e-06	-1.06e-05	-9.83e-07	-9.86e-06	-1.48e-05	-2.38e-05	-7.23e-06
	(1.12e-05)	(1.67e-05)	(1.28e-05)	(1.34e-05)	(1.64e-05)	(3.37e-05)	(1.19e-05)
HQ	1.011	0.752	0.405	1.716	-3.028***	5.188	0.358
	(0.943)	(1.433)	(1.043)	(1.123)	(1.082)	(3.188)	(0.967)
INDDENS	0.000657	0.00114	-0.000766	0.000530	0.000877	0.000306	0.000350
	(0.000860)	(0.00143)	(0.000867)	(0.00108)	(0.000963)	(0.00264)	(0.000914)
IND	-2.38e-07	-3.35e-08	-3.70e-07	-1.98e-07	-1.93e-05*	-6.62e-06	-1.71e-07
	(8.53e-07)	(1.17e-06)	(1.11e-06)	(9.18e-07)	(9.84e-06)	(2.57e-05)	(8.13e-07)
STUD	5.92e-07	3.01e-07	-1.21e-07	1.01e-06	-3.67e-06**	2.00e-06	2.19e-07
	(1.09e-06)	(1.68e-06)	(1.19e-06)	(1.28e-06)	(1.42e-06)	(4.06e-06)	(1.11e-06)
R&D	-0.00103	-0.00308	-5.71e-05	-0.000499	-0.00589*	-0.000145	-0.00145
	(0.00282)	(0.00410)	(0.00328)	(0.00330)	(0.00315)	(0.00814)	(0.00300)
SIZE	0.142**			0.132*	0.134	0.258	0.0874
	(0.0645)			(0.0766)	(0.0952)	(0.278)	(0.0675)
KIS	0.0139	-0.000386	0.0315			0.0655	0.0172
	(0.0827)	(0.126)	(0.0973)			(0.230)	(0.0905)
AGE	-0.0677**	-0.0828	-0.0231	-0.0664**	-0.0606**		
	(0.0265)	(0.0575)	(0.0329)	(0.0328)	(0.0241)		
Constant	0.0289	0.419**	0.180	0.0322	0.190	0.0239	0.0546
	(0.105)	(0.201)	(0.187)	(0.104)	(0.134)	(0.354)	(0.113)
Obs.	216	144	72	178	38	42	174
R-squared	0.045	0.042	0.059	0.043	0.238	0.065	0.041

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As model I in Table 6 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 GPTs such as nanotechnology to develop and inhibits possibilities of catalysing effects and cross fertilisation. The differentiation into different subgroups emphasizes that, however, this effect differs across different firm characteristics: The results for the independent variable of *LQ* are still significantly negative coefficients for high-KIS and older firms (see Table 6: model IV and VII). These are the firms that are especially prone to exploitation activities since they are knowledge-intensive and hence close to research and development. It might hence be the case that knowledge intensive firms explore the nano-field as their flexibility of thinking might make it more easy for those firms to perceive possibilities of application of old nano-knowledge in new fields. Another interesting issue is that *HQ* shows statistically insignificant coefficients, except in the case of low-KIS. An explanation for this issue might be that *HQ* is captured by the specialization measures. We also know from Table A1 that *HQ* and *LQ* are correlated with each other (r=0.2296***). In the case of low-KIS we even find a strong significant coefficient with a negative sign. We interpret this as a statistical support for the fact, that firms where knowledge is not a crucial driver of employment growth depend less on high qualified employees (as knowledge sources) in the region.

Since 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 since they occupy mostly specialised niches when entering the market. This is why *H2* can be confirmed and *H2a* cannot.
In order to test *H2b*, we also included the squared form of *LQ* (LQ^2) 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 specialised. 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). Since this does only hold for one particular case, *H2b* cannot be confirmed here. This might be due 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.
Summarising, 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. Hypotheses 2 can therefore be confirmed in general means.

4.3 Robustness of the impact of specialization (Hypothesis 3)

In a last step, we analyse the robustness of the impact of specialization (*LQ*, LQ^2) and the location characteristics (*HQ, INDDENS, IND, STUD, R&D*) 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*, *LQ²* and the different *LOCATION* measures. Hence, we hypothesise that *the impact of specialization on employment growth in nanotechnology firms is robust across a year-to-year consideration.* Table A3 presents the detailed regression results for the fixed effects model. Again, Table A1 clearly presents that *LQ* and *LQ²* (r=-0.4078) are highly correlated. We already stated in hypothesis 1 (section 4.1) that firms in nanotechnology are affected by location-specific characteristics (e.g. *HQ*, *INDDENS*, *IND*, *STUD*, *R&D*). Thus, we neglect these indicators because in this analysis it is beyond the scope to analyse the pure impact of location again. Now we only consider the more particular impact of the level of specialization. The findings vary (see Table 7).

Table 7: Cross-sectional time series – fixed effects model for employment growth (EMP)

Variables	(I) EMP	(II) EMP	(III) EMP	(IV) EMP	(V) EMP	(VI) EMP	(VII) EMP
LQ	-0.00255	-0.00308	0.00293	-0.00318	0.00214	0.000888	0.000158
	(0.00181)	(0.00217)	(0.00276)	(0.00199)	(0.00557)	(0.00823)	(0.00167)
LQ²	-3.14e-05*	-4.13e-05**	2.18e-05	-3.37e-05*	9.27e-06	-0.000142	-7.05e-07
	(1.67e-05)	(2.02e-05)	(2.36e-05)	(1.79e-05)	(5.99e-05)	(8.71e-05)	(1.50e-05)
HQ	1.551***	2.328***	0.366	1.476***	1.902***	2.719**	1.223***
	(0.283)	(0.404)	(0.242)	(0.328)	(0.527)	(1.266)	(0.228)
INDDENS	0.00463	0.000657	0.00504	0.00105	0.0204	0.00253	0.00528
	(0.00809)	(0.0120)	(0.00643)	(0.00916)	(0.0164)	(0.0351)	(0.00652)
IND	-1.09e-05	-3.83e-05	-2.78e-05	3.26e-06	-0.000100	3.48e-05	-2.79e-05
	(2.76e-05)	(3.98e-05)	(2.46e-05)	(3.07e-05)	(6.55e-05)	(0.000168)	(2.17e-05)
Constant	8.224***	8.388***	9.505***	8.106***	8.694***	8.705**	8.097***
	(0.791)	(1.148)	(0.664)	(0.902)	(1.631)	(3.731)	(0.631)
Obs.	652	429	223	538	114	131	521
R-squared	0.076	0.125	0.026	0.070	0.173	0.131	0.078
Number of id	652	429	223	538	114	131	521

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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 *LQ²* in the overall model I and two subsamples of high-KIS and small firms. 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 indeed influences firm employment growth in a non-linear way (see Table 7). While 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 or too less specialised. 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 that come together with average growth are not usually related to occurrence of year-to-year growth. However, an analysis of the year-to-year growth process of nano-firms provides additional information, as discussed above. If we change the perspective from average growth to year-to-year consideration the finding 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 sensibility of cluster-policies in a GPT-context our results question the adequacy of such policy instruments – although further empirical investigation needs to be done to further disentangle the concrete effects of specialization on firm growth in high – and nanotechnologies.

5 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. While the share of highly qualified employees never hampers growth (although it seems not to advance it either in e.g. larger firms), the local stock of employees concerned with R&D indeed 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 analysing 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 specialised 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) in order 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 paper to investigate the mechanisms behind our findings. It would be interesting to know how exactly local knowledge is processed, where spillovers indeed are effective and how specialization exactly affects innovation in high-technologies.
The conclusion of this paper remains that local knowledge endowment indeed positively influences firm growth in nanotechnology, while local knowledge specialization surely is not always positively affecting the growth of individual firms. Cluster policies should therefore at least be considered carefully.

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Appendix

Table A1: 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