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Firm Performance in the Periphery: On the Relation between Firm-Internal Knowledge and Local Knowledge Spillovers

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Markus Grillitsch and Magnus Nilsson

Abstract

This paper challenges one of the fundamental propositions within economic geography; that location in knowledge regions contributes to firm performance in general and especially for knowledge intensive firms that compete on the basis of knowledge. Our analysis of Swedish micro-data on 32,535 firms from 2004-2011 provides evidence that knowledge intensive firms benefit less from local knowledge spillovers than firms with comparably low in-house knowledge. This suggests that firms with high internal competencies can compensate for a lack of local knowledge spillovers and that negative knowledge externalities may make location outside knowledge centers more beneficial for such firms.

JEL codes: R10; R11; O30

Keywords: periphery, firm performance, spillovers, agglomeration

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Abstract

One of the most established arguments in regional studies is that knowledge dynamics shape the geography of economic activities and, more specifically, that knowledge intensive activities benefit from collocation due to knowledge spillovers, local buzz and access to labor. This implies that knowledge-intensive firms should be less competitive in regions with low knowledge intensity. There are, however, competing arguments that knowledge intensive firms suffer more from negative spillovers and are less dependent on local knowledge sources than often presumed. This paper investigates these competing propositions based on Swedish micro-data comprising 32,535 firms from 2004-2011. It provides strong evidence for a negative relationship between the knowledge intensity of firms and local knowledge spillovers. While firms with weak internal knowledge grow faster in knowledge intensive regions, this growth difference disappears or is even reversed for knowledge intensive firms.

Key words: Periphery, firm performance, spillovers, agglomeration, knowledge intensive firms

JEL codes: R10; R11; O30

1 Introduction

A widely held view in both research and policy is that firms, and especially knowledge intensive firms, thrive in knowledge-rich regions or clusters because of the existence of knowledge spillovers, access to local labor markets and local buzz (STORPER and VENABLES, 2004; AUDRETSCH and DOHSE, 2007). This argument ties in with the debate on the learning and knowledge-based economy, which suggests that knowledge is a key driver for economic development (LUNDVALL and JOHNSON, 1994; COOKE and LEYDESDORFF, 2006). Understanding the main determinants for and effects of knowledge exchange and learning has therefore featured prominently on the research agenda.

In this context, the role of different forms of proximity has been discussed extensively. While geographical proximity alone is neither sufficient nor necessary for knowledge exchange to take place (BOSCHMA, 2005), distinct institutional, technological and social contexts often intersect in close geographical proximity (HASSINK and KLAERDING, 2012). Empirical evidence suggests that geographical proximity, in combination with other forms of proximity, exerts a significant influence on knowledge exchange (PACI et al., 2014). A common view in the literature on economic geography, holds that firms with high levels of in-house knowledge should benefit most from knowledge externalities. This implies a self-reinforcing mechanism between knowledge intensive firms and regions, very much in line with Malmberg and Maskell's (2002, 2006) knowledge-based theory of spatial clustering. This view entails a lackluster outlook for knowledge intensive firms located in the knowledge periphery, and this view has come to influence economic policy in many countries (SHEARMUR, 2012)[1].

[1] As the focus of this paper is on knowledge externalities and the geography of knowledge the term 'periphery' refers to *knowledge* periphery rather than for example administrative or population periphery (though these are of course highly correlated). The implication from this is that even densely populated regions can be in the knowledge periphery if they have a low level of knowledge intensity. The motivation for focusing on knowledge intensity stems from our focus on the debate on knowledge intensive firms and knowledge based externalities, which is prevalent in the literature.

However, all too often important differences between firms, i.e. firm heterogeneity, are ignored (e.g. SRHOLEC and VERSPAGEN, 2012). In fact, few studies address the question of which type of firms benefits most from being located in knowledge intensive regions (MCCANN and FOLTA, 2008; ERIKSSON, 2011).

This paper challenges the dominant view accounted for above. Instead, we elaborate conceptually why knowledge intensive firms may benefit to a lesser extent from local knowledge spillovers (LKS) than firms with comparably lower in-house competencies. Firstly, negative knowledge externalities may negatively affect the performance of knowledge intensive firms located in knowledge dense regions (SHAVER and FLYER, 2000; ALCÁCER, 2006; MARIOTTI et al., 2010). Secondly, knowledge intensive firms will be more able to compensate for a lack of LKS by acquiring knowledge from distanciated ties (GRILLITSCH and NILSSON, 2015; JAKOBSEN and LORENTZEN, 2015).

The paper then investigates these competing arguments empirically; i.e. whether the interrelation between firm knowledge intensity and LKS is positively or negatively related to firm growth. Differently put, do knowledge intensive firms benefit more from location in knowledge dense regions than firms with low knowledge intensity? In order to analyze whether the positive or negative effects of the interplay between firm-internal knowledge and LKS prevail, a quantitative analysis is conducted using Swedish micro data on 32,535 firms in the period 2004-2011.

The paper is structured as follows: Chapter two provides a review of the literature on proximity and knowledge spillovers. It accounts for the theoretical arguments as to why location in knowledge dense regions should contribute to firm performance and introduces arguments for the opposite. Then, firm heterogeneity is introduced and the interplay between firm-internal knowledge and LKS is discussed. In chapter three, the empirical study is presented and in chapter four the results are discussed. Chapter five presents the robustness tests. The final chapter comprises conclusions, limitations and avenues for future research.

2 Literature review and theoretical framework

Proximity and knowledge spillovers

The last decades have witnessed a vast interest in regional knowledge dynamics and how these dynamics relate to firm performance. While different strands of literature place emphasis on different mechanisms (networks, labor mobility, knowledge externalities, institutional proximity and local buzz) there is wide agreement that firms benefit from being located in knowledge intensive regions (DÖRING and SCHNELLENBACH, 2006; AUDRETSCH and DOHSE, 2007). However, as pointed out by Eriksson (2011) many empirical studies focus primarily on mapping spillovers rather than analyzing the extent to which proximity to external knowledge affect the performance of firms.

One explanation for the benefits derived from location in knowledge dense regions has to do with the spatial boundedness of tacit knowledge due to the contextualized and 'sticky' nature of such knowledge (MALMBERG and MASKELL, 1999; ASHEIM and ISAKSEN, 2002; STORPER and VENABLES, 2004). This literature emphasizes the role of collective learning, and spillover of tacit knowledge that takes place in regions where a large number of knowledge-intense firms and organizations are collocated (FLORIDA, 1995; MALMBERG and MASKELL, 2006; BELUSSI and SEDITA, 2010; HEALY and MORGAN, 2012). In this view, the benefits of clustering stem from face-to-face exchange, mutual trust, and shared socio-cultural and institutional context (MASKELL, 2001; HEALY and MORGAN, 2012; NILSSON and MATTES, 2015) as well as from a greater flow of codified information (GERTLER, 2003), an increased ability to collectively assess and evaluate external knowledge and information collectively within a cluster (MASKELL, 2001; DÖRING and

SCHNELLENBACH, 2006), and creation of markets for knowledge and knowledge exchange (ANTONELLI et al., 2011).

More recently, however, research has increasingly challenged this view. In a review of the literature on clusters, Malmberg and Power (2005) find little support for the argument 'that organized local inter-firm cooperation and transactions characterize successful firms' (p.425). Similarly, Huber (2012) finds that technological knowledge spillovers within clusters are limited and do not seem to generate significant advantages, even for knowledge intensive firms. Following this, focus has more and more shifted to the role of labor market dynamics . Authors in this stream argue that the main mechanism of LKS is the mobility of skilled labor and inventors rather than the tacitness and embeddedness of knowledge (BRESCHI and LISSONI, 2001, 2009). This literature thus focuses less on 'pure' knowledge externalities and more on the clustering of R&D and the diffusion of knowledge through local mobility of skilled labor and inventors. Studies have found that local labor market externalities and labor pooling have a strong positive effect on firm performance and regional growth (BOSCHMA et al., 2014) and that these effects are stronger than those from regional co-location, diversity and scale (ERIKSSON and LINDGREN, 2009).

While many studies focus on the positive effects from location in knowledge-dense regions, a number of studies also acknowledge potential negative or offsetting effects (e.g. ANTONELLI et al., 2011). In highly specialized regions with a vibrant local buzz and strong LKS, the long-term innovativeness of firms may be challenged by the development of an increasingly homogenized knowledge base. One reason for this is the risk of lock-in and loss in creativity if the LKS are strong and extra-regional pipelines are lacking (BATHELT et al., 2004). The existence of extra-local knowledge pipelines are therefore seen as instrumental in overcoming risks of lock-in and inertia (CAMAGNI, 1995; HASSINK, 2005; TRIPPL and OTTO, 2009; BRESCHI and LENZI, 2013). However, even with the existence of extra-regional pipelines there are negative knowledge externalities associated with the clustering of skilled labor, for example leading to an increased risk of labor poaching and leakage of knowledge (COMBES and DURANTON, 2006; ANGELI et al., 2013). In this regard, Mariotti et al. (2010) find that negative LKS may deter multinational corporations from agglomerating with domestic companies as knowledge inflow may be lower than knowledge outflow. Similarly, in a study on the Bangalore IT cluster Angeli et al. (2013) find that labor poaching tend to flow from MNC to local domestic firms and that there is a strong tendency to source labor from local rivals.

In summary, while a number of negative effects from too strong regional concentration of knowledge have been identified, the basic contention that location in knowledge rich environments is conducive for firm performance is widely accepted. This is the case regardless whether the spatial boundedness of knowledge is understood in terms of spatially bounded flows of 'sticky' (tacit) knowledge within a locality or as the localized labor markets of highly trained individuals.

Firm heterogeneity and local knowledge spillovers

While the general importance of LKS for firm performance is well established theoretically and empirically, we know considerably less about what type of firms benefits most from knowledge externalities in agglomerations. A broad reading of the literature suggests that firms with high in-house capacities benefit most from being located in a knowledge rich region, i.e. that firms complement their in-house knowledge with knowledge available in close proximity. At the same time it is widely accepted that firms with a strong internal knowledge base also have the ability to source knowledge from non-local sources because of their greater absorptive capacity (i.e. to compensate for lacking LKS). By this logic, firms with relatively weaker in-house knowledge (i.e. lower absorptive capacity) should be more dependent on LKS as they are less able to build knowledge pipelines. The level of absorptive capacity thus greatly influences a firm's ability to compensate and/or complement their internal knowledge with local or global knowledge. The absorptive capacity of firms in combination with the existence of positive as well as negative knowledge externalities can thus be expected to influence the growth of firms.

As regards the complementary nature of in-house knowledge and LKS, one argument brought forward is that knowledge-intensive firms that compete on the basis of complex and advanced knowledge have most to gain from a location in knowledge dense regions and therefore should be among the most heavily agglomerated (HEALY and MORGAN, 2012). Also, it is argued that firms with a higher level of internal knowledge are more attractive as partners to exchange knowledge with than firms with a low level of internal knowledge (TER WAL and BOSCHMA, 2011).

> The crucial assumption we make here is Arrow's (1962) argument that knowledge spillovers are more important in, and reflected at least to some degree by, highly R&D intensive industries. By contrast, such knowledge externalities, while perhaps still present, play a less important role where the creation of new economic knowledge, as reflected by R&D intensity, is negligible. Thus, the location of production would be more concentrated in those industries where knowledge spillovers are prevalent, that is in industries which are R&D intensive. (AUDRETSCH and FELDMAN, 1996, 634)

In line with this, Audretsch and Dohse (2007, 98) find that 'the growth of knowledge intensive firms is higher in regions with a high agglomeration of knowledge assets […] however, this does not appear to be the case in the low-knowledge sectors'. They explain this not only by the relative importance of LKS for knowledge-intensive firms, but also by their greater ability to identify, evaluate, access and use knowledge form outside the confines of the firm itself, i.e. their absorptive capacity, which is largely determined by the level of related in-house knowledge (COHEN and LEVINTHAL, 1990; ZAHRA and GEORGE, 2002). It has been argued that the absorptive capacity of firms is further reinforced by a location in a dense knowledge environment (MASKELL, 2001; GERTLER, 2003). Consequently, this would further increase the positive effect of being located in a knowledge rich region (DÖRING and SCHNELLENBACH, 2006) and it could therefore be expected that ‘firms with higher absorptive capacities should be able to benefit more from available knowledge spillovers…’ (MCCANN and FOLTA, 2008, 554).

Another argument is put forward by Baldwin and Okubo (2006) who approach firm heterogeneity and agglomeration by building on models developed in the literature on new economic geography. They argue for the existence of two forces, agglomeration effects related to linkages along the value chain and dispersion forces related to competition. The most competitive firms will be least affected by a high degree of competition, i.e. dispersion forces will be low for such firms, while benefiting most from agglomeration. Baldwin and Okubo thus find that the strongest firms will benefit most from a location in an agglomeration.

While the above represents the dominant view within economic geography, there are also contrasting arguments that emphasize that knowledge intensive firms may also suffer disproportionally from negative knowledge externalities. A key argument in this regard is based on the fact that firms are not only receivers but also sources of knowledge spillovers (ANGELI et al., 2013; FRISHAMMAR et al., 2015). Collocation and direct interaction not only facilitate the transfer of complex knowledge but also tend to exacerbate the risk of negative knowledge externalities in the form of knowledge leaking (SAMMARRA and BIGGIERO, 2008). Firms located in dense knowledge regions are thus more exposed to knowledge leakage and this is especially the case for firms with leading in-house knowledge since they do not benefit from the spillover of inferior knowledge while they lose if their advanced knowledge spills over to competitors (SHAVER and FLYER, 2000; ALCÁCER, 2006; MARIOTTI et al., 2010). In line with this argument, Alcácer and Chung (2007) find that 'leader' firms collocate in areas with high academic excellence while avoiding industry clusters.

A related negative effect from location in dense knowledge regions has to do with labor poaching, i.e. the loss of qualified human capital to competitors and increased labor costs. Labor poaching is the flipside of the positive effects from labor market pooling. Combes & Duranton (2006) apply a game theoretical approach to illustrate two costs associated with labor poaching: [1] that competitors gain access to the firm's knowledge by poaching from its workforce and [2] increased labor costs as firms are forced to raise wages to retain its workers. Based on this they introduce a model that implies that "…labour market pooling and spill-overs can no longer be viewed as distinct motives for agglomeration since technological spill-overs may percolate through the labour market." (COMBES and DURANTON, 2006 p.4). They show that especially in situations of intense rivalry (such as in knowledge centers) labor costs of strategic workers tend to increase so that the costs of poaching outweigh the benefits of pooling (i.e. negative knowledge externalities increase and positive knowledge externalities decrease). .

Angeli et al. (2013) find that labor tend to flow from MNCs to local clustered firms rather than vice versa largely because MNCs possess refined knowledge that can upgrade local firms. Similarly, Alsleben (2005) argues that it is particularly firms with higher level knowledge that are affected by negative aspects of clustering in the form of labor poaching:

> "While a 'poor' firm certainly benefits from the 'good' one, the good one may be concerned with making its rival stronger while not receiving any benefit itself and may thus have not incentive to co-locate." (1993; ALSLEBEN, 2005 p.218)

These negative externalities may offset the positive effects associated with LKS in core regions, especially for highly knowledge intensive firms. Based on this it can be argued that knowledge intensive firms may benefit from location in the knowledge periphery. However, in order for knowledge intensive firms to flourish in the knowledge periphery they must arguably be able to compensate for the lack of LKS through strong in-house knowledge and/or non-local ties (e.g. global pipelines). Grillitsch and Nilsson (2015) find evidence that innovative firms in peripheral regions compensate for lacking LKS by engaging in collaborations and that this is especially the case for knowledge intensive firms with a high absorptive capacity. Similar findings have been reported by Jakobsen and Lorentzen (2015). Hence, because of their relatively higher absorptive capacity strong firms can overcome geographical distance to external knowledge sources while this is more difficult for weak firms. Furthermore, it has been argued that extra-regional knowledge sources contribute more to a firm's innovativeness and competitiveness than regional ones (FITJAR and RODRÍGUEZ-POSE, 2011). This relates to the observation that some types of innovation may be more likely in the remote areas in the knowledge periphery than in core regions (DOLOREUX and SHEARMUR, 2012).

In summary, while the prevailing view in the literature seems to be that knowledge dense regions especially benefit firms with strong internal knowledge, this is not uncontested. As presented above, both conceptual and empirical work indicates that knowledge intensive firms may suffer disproportionally from negative knowledge externalities. There are thus both positive and negative effects of the interrelationship between LKS and firm-internal knowledge on firm performance. If the positive effects outweigh the negative, the performance gap of knowledge intensive firms located in the knowledge center as compared to the periphery would widen, i.e. such firms would grow faster in knowledge centers. On the other hand, if the negative effects dominate, the performance gap would diminish, possibly even to the extent that knowledge intensive firms grow equally or faster in the knowledge periphery.

3 Empirical Study

The data

The empirical study is based on data provided by Statistics Sweden. The data covers all firms and individuals registered in Sweden. From the longitudinal individual database (LISA), we use variables for occupation, education, and location of individuals. The individual database is merged with the database on business statistics (FEK), which supplies us with control variables relating to the financial situation, investments, and industry codes of firms. Each firm is then linked to the firm register that allows us to locate the firms' headquarters in one of 290 Swedish municipalities. Finally, we use data provided by the Swedish Transport Authority about the travel distance between the municipalities in order to calculate the regional variables.

The analysis is based on data from 2004 to 2011. The choice of the time period is largely based on the availability of occupational data, which is central for our measurement of regional and firm-level knowledge. Micro-firms are excluded because many such firms have no growth ambition. For instance, micro firms include academics who offer some consulting services but have no employees. Micro firms also include many small services and kiosks. In order to ensure comparability, the EU definition for micro-firms is used, i.e. firms with less than 10 employees on average over the time period are excluded. Furthermore, firms that have changed location during the observation period are excluded as this implies a change in the accessibility to knowledge available in the region, the causes and effects of which can relate to other factors not investigated in this study. Finally, public services, activities of households as employers and extraterritorial organizations, which include embassies or offices of the

United Nations (SNI codes 84 to 89, and 97 and above) are excluded because the investigated relationships and measures are meaningless for such organizations.

Variables

The dependent variable is firm performance measured as employment growth (e_growth) and sales growth (s_growth) in % as follows:

$$e\_growth_{it} = (ln(employment_{it+1}) - ln(employment_{it+0})) \times 100 \qquad (1)$$

$$s\_growth_{it} = (ln(sales_{it+1}) - ln(sales_{it+0})) \times 100 \qquad (2)$$

where i denotes $1,\ldots,n$ firms and t the year of observation.

The independent variables relate to the knowledge intensity of firms and regions. Individuals conducting knowledge intensive activities are identified through occupational data. The use of occupational data has several advantages, as compared to educational, patent or R&D statistics. Educational data can be out-dated and does not necessarily reflect what type of work individuals are actually conducting. This means that occupational data has a greater potential to capture on-the-job-training and shifts in specialization of individuals since their time of graduation. Compared to R&D and patent data, occupational statistics is less biased towards larger firms and specific patent intensive sectors (JACOBSSON et al., 1996; BROUWER and KLEINKNECHT, 1999). With occupational statistics it is possible to relatively accurately identify highly skilled individuals who perform knowledge intensive activities.

The occupational data is provided by Statistics Sweden and comprises all individuals registered in Sweden. The Swedish Standard Classification of Occupations (SSYK) provides the basis for occupational characteristics. This is based on a classification along two dimensions: [1] the type of work (i.e. the set of tasks that are performed by an employee), and [2] the skills required to perform the work. The data thus contains an implicit educational dimension, i.e. the level of education *usually* required to perform the tasks. Individuals who perform knowledge intensive activities are defined as:

- All employees registered as physical, mathematical and engineering science professionals. Individuals in this category have a skill level equivalent to at least three to four years of higher education and an academic degree[2].
- Employees registered as research and development managers.
- Employees registered as corporate managers that also have more than 2 years of university training in a technological field including science, mathematics and computing as well as engineering, manufacturing and construction.
- Employees registered as managers of small enterprises that also have more than 2 years of university training in a technological field including science, mathematics and computing as well as engineering, manufacturing and construction.

The firm-internal knowledge intensity for firm i at time t ($f\_intensity_{it}$) is measured as the share of individuals conducting knowledge intensive activities ($qualified_{it}$) in the total number of employees ($employment_{it}$):

$$f\_intensity_{it} = qualified_{it}/employment_{it} \times 100 \qquad (3)$$

The regional knowledge intensity is measured as the share of individuals conducting knowledge intensive activities in the total number of individuals working in the region.

[2] The focus on technological or scientific knowledge intensity (physical, mathematical and engineering science professionals) is motivated by the fact that many studies on the geography of knowledge and LKS have focused on the mobility of such labor, patenting and R&D (which is closely linked to this type of knowledge).

Because the Swedish municipalities differ greatly in size and population, the regional measure includes spillovers from other municipalities. The largest municipality is more than 19,000 km^2 while the smallest one is confined to less than 9 km^2. The most populated municipality counts more than 750,000 inhabitants while the smallest is home to only approximately 2,500 inhabitants. The municipalities in the main urban areas, especially Stockholm, are small but heavily populated while the municipalities in northern Sweden are large in area but sparsely populated. Hence, to simply use municipal values would strongly distort the results, which can be avoided by considering spillovers from other municipalities as follows:

$$r\_intensity_{mt} = \frac{\left(qualified_{mt} + \sum_{s=1}^{n} qualified_{st} e^{-\lambda t_{ms}}\right)}{\left(employment_{mt} + \sum_{s=1}^{n} employment_{st} e^{-\lambda t_{ms}}\right)} \times 100 \quad (4)$$

$r\_intensity_{mt}$ denotes the regional knowledge intensity for municipality $m = 1,\ldots,290$ at time t. To the number of individuals conducting knowledge intensive activities in each municipality $qualified_{mt}$ the spillovers from neighbouring municipalities are added. $qualified_{st}$ stands for the number of individuals performing knowledge intensive activities in other municipalities $s = 1, \ldots, 289$. The spillovers from other municipalities are diminished using an exponential time-distance decay function (HANSEN, 1959). λ represents a sensitivity parameter with respect to the time-distance between two municipalities m and s denoted by t_{ms}. The time-distance is measured as driving time in minutes by car using the most efficient route in 2004. The denominator is the sum of employment in municipality m ($employment_{mt}$) and the spillovers of employment from other municipalities s ($employment_{st}$) applying the same time-distance decay function as above. As a baseline for our study, λ is set to 0.017 in line with other studies conducted in Sweden (HUGOSSON, 2001; ANDERSSON and EJERMO, 2005; GRILLITSCH and NILSSON, 2015). However, the robustness of the results is tested by running the models with other values for λ.

The capacity of firms to finance growth is controlled for by including the percentage share of cash flow in turnover. The total investments of firms is accounted for in million Swedish Kronor divided by the number of employees. Agglomeration effects are captured by introducing a dummy variable, which is set to 1 for firms that are located in Stockholm, Gothenburg or Malmö. Firm size is accounted for by the logarithm of total employment. Industry specific growth differences are controlled for by introducing dummies for two-digit industry codes.

Table 1 presents the descriptive statistics for the variables as used in the models. The data includes 185,337 observations for 32,535 firms. The mean employment growth is 2.7% and the mean sales growth 7.0%. The regional knowledge intensity is observed in all 290 municipalities in 7 years, resulting in 2,030 observations. The average regional knowledge intensity is 4.2%. The average knowledge intensity at the firm level is slightly higher with 4.8%. The mean cash-flow of firms in turnover amounts to 5.7%. Investments of firms are on average 58,000 Swedish Kronor per employee. Approximately 25% of the firms are located in the urban centres Stockholm, Gothenburg or Malmö. The average firm size is 55 employees. The correlations can be found in annex 1.

Table 1 Descriptive statistics

Variables	Observations	Mean	Standard deviation	Min	Max
Employment growth (%)	185,337	2.73	20.90	-99.85	99.85
Sales growth (%)	185,337	7.01	26.06	-119.98	119.99
Regional knowledge intensity (%)	2,030	4.21	1.14	1.71	7.58
Firm knowledge intensity (%)	185,337	4.79	14.86	0.00	100.00
Finance (%)	185,337	5.70	110.98	-24100.09	9692.29
Investments	185,337	0.58	4.80	-1.15	1351.95
Metropolitan area (dummy)	185,337	0.25	0.43	0.00	1.00
Number of employees	185,337	55.24	311.70	1.00	22347.00

Note: Regional knowledge intensity is observed for all 290 Swedish municipalities in 7 years.

The model

The specification of the econometric model to be estimated relates the dependent variable, firm growth, to predictor variables as follows:

$$growth_{it} = \alpha r\_intensity_{mt} + \beta f\_intensity_{it} + \gamma controls_{it} + \omega z_t + \varepsilon_{it} \qquad (5)$$

where i is a firm, m is a region, and t is time. Growth of a firm ($growth_{it}$) is the function of the regional knowledge intensity ($r\_intensity_{mt}$), firm knowledge intensity ($f\_intensity_{it}$), a vector of control variables ($controls_{it}$), temporal shocks (z_t), and errors (ε_{it}). The vector of control variables includes financial capacity, investments, the logarithm of firm size, a dummy for location in a metropolitan area, and industry dummies. The above model is estimated using pooled OLS[3]. Given that the data has a panel structure we account for unobserved effects at the firm-level relating to time-constant characteristics such as firm routines, or managerial qualities as follows:

$$growth_{it} = \alpha r\_intensity_{mt} + \beta f\_intensity_{it} + \gamma controls_{it} + \omega z_t + c_i + u_{it} \qquad (6)$$

Where c_i are the unobserved effects at the level of the firm and u_{it} are the idiosyncratic errors with the usual properties (mean 0, uncorrelated with itself, uncorrelated with the other independent variables, uncorrelated with c_i, and homoscedastic). A choice has to be made whether to use fixed or random effects. Fixed effects, in contrast to random effects, do not assume that the unobserved effects are uncorrelated with the other independent variables. However, fixed effects require substantial variation over time. At the firm level, growth and to some extent also firm knowledge intensity varies over time. However, the variation is much lower for regional knowledge intensity. While the regional knowledge intensity has slightly

[3] As pooled OLS is sensitive to outliers, the raw data is corrected by removing extreme outliers as regards growth, i.e. all observations that are below or above three standard deviations as calculated for the dependent variables of the raw data. Also, the findings of the study are not qualitatively affected when estimating a quantile regression, which is robust against outliers.

increased over time, the municipalities show very similar patterns of change. As the change is of about the same magnitude in all years and for all municipalities, there is too little variety over time to use fixed effects and therefore the random effects are used (STATA, 2013, 359-387).

4 Results

Table 2 presents the results for the regressions on firm employment and sales growth. Our results provide strong support for the alternative hypothesis, i.e. that there is a negative interdependency between LKS and in-house knowledge. Firms with weak in-house knowledge grow faster in knowledge intense regions while there is no evidence that firms with high in-house knowledge do so. Models 1, 2 and 3 refer to regressions on employment growth using the pooled OLS estimator. According to model 1, regional and firm knowledge intensity show a positive and highly significant relationship with employment growth. A 10% increase in knowledge intensity of firms is associated with a 0.5% increase in employment growth. As the mean employment growth is 2.7% such an increase corresponds to almost 20% as compared to the mean.

The coefficient for regional knowledge intensity is more difficult to interpret. The regional knowledge intensity for a firm located in Stockholm is 6.9% (average from 2004-2011), which is high as compared to smaller urban regions such as Lund, Karlskrona or Kiruna, where the regional knowledge intensity is 4.7%, 3.4% or 2.5% respectively. It follows from this that firms located in Stockholm are associated with 0.4% higher growth than firms in Lund, 0.6% higher growth than firms in Karlskrona and 0.8% higher growth than firms in Kiruna.

It may well be argued that the relationship between firm and regional knowledge intensity and firm growth is not linear[4]. The presence of non-linearity was assessed by including the squared terms in the regression, testing their significance and comparing the AICs and BICs of the different models. According to this analysis, non-linearity is present in the data for firm-level knowledge intensity but not for the regional level. Model 2, therefore, includes the square of firm knowledge intensity, which shows a highly significant negative sign, implying decreasing marginal returns of firm knowledge intensity.

Model 3 includes the interaction term between the regional and firm knowledge intensity. Interestingly the interaction term is negative and highly significant, thus supporting the alternative hypothesis. The meaning of the interaction term is that the effect of the regional knowledge intensity decreases for firms with a higher level of in-house knowledge. The total effect of the regional knowledge intensity turns negative for firms with knowledge intensity higher than 30%.

Models 4, 5 and 6 show the results for the pooled OLS regressions on sales growth. The results are qualitatively very similar to the ones for employment growth, although the effect of technology intensity at the level of the firm and the region appear somewhat smaller. The interaction term in model 4 is also highly significant and negative; corroborating the general picture of a negative interrelation between LKS and in-house knowledge. The point, when the total effect of the regional knowledge intensity turns from positive to negative, lies at a firm knowledge intensity of 22%. The average firm knowledge intensity is 4.8% and approximately 8%, that is 2,540 firms in our sample, have a knowledge intensity of more than 25%.

[4] We thank an anonomous reviewer for pointing this out.

Table 2 Relationships between firm employment and sales growth, firm and regional knowledge intensities at λ = 0.017

	Pooled OLS						Firm random effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	e_growth	e_growth	e_growth	s_growth	s_growth	s_growth	e_growth	e_growth	e_growth	s_growth	s_growth	s_growth
Regional KI	0.175***	0.164***	0.194***	0.127**	0.122**	0.155**	0.259***	0.246***	0.293***	0.168**	0.164**	0.235***
	(0.0474)	(0.0474)	(0.0487)	(0.0592)	(0.0593)	(0.0608)	(0.0698)	(0.0698)	(0.0713)	(0.0818)	(0.0819)	(0.0837)
Firm KI	0.0480***	0.123***	0.156***	0.0365***	0.0691***	0.105***	0.0489***	0.137***	0.187***	0.0279***	0.0554***	0.132***
	(0.00462)	(0.0118)	(0.0170)	(0.00577)	(0.0148)	(0.0212)	(0.00605)	(0.0149)	(0.0216)	(0.00729)	(0.0181)	(0.0262)
Firm KI x Firm KI		-0.000997***	-0.000948***		-0.000434**	-0.000381**		-0.00115***	-0.00108***		-0.000359*	-0.000252
		(0.000145)	(0.000147)		(0.000182)	(0.000183)		(0.000177)	(0.000179)		(0.000217)	(0.000219)
Regional x Firm KI			-0.00644***			-0.00703**			-0.00975***			-0.0149***
			(0.00236)			(0.00295)			(0.00303)			(0.00367)
Finance	0.00136***	0.00140***	0.00139***	-0.00251***	-0.00250***	-0.00250***	0.00151***	0.00153***	0.00153***	-0.00398***	-0.00397***	-0.00398***
	(0.000433)	(0.000433)	(0.000433)	(0.000541)	(0.000541)	(0.000541)	(0.000476)	(0.000476)	(0.000476)	(0.000591)	(0.000591)	(0.000591)
Investments	0.0895***	0.0878***	0.0878***	0.0669***	0.0662***	0.0662***	0.0960***	0.0947***	0.0945***	0.0611***	0.0606***	0.0603***
	(0.0101)	(0.0101)	(0.0101)	(0.0126)	(0.0126)	(0.0126)	(0.0113)	(0.0113)	(0.0113)	(0.0140)	(0.0140)	(0.0140)
Size	-3.292***	-3.323***	-3.321***	-1.550***	-1.563***	-1.561***	-6.292***	-6.327***	-6.322***	-2.320***	-2.331***	-2.323***
	(0.0536)	(0.0538)	(0.0538)	(0.0670)	(0.0672)	(0.0672)	(0.0758)	(0.0760)	(0.0761)	(0.0899)	(0.0901)	(0.0902)
Metropolitan area	1.068***	1.059***	1.074***	0.641***	0.637***	0.654***	1.493***	1.477***	1.498***	0.784***	0.779***	0.812***
	(0.141)	(0.141)	(0.141)	(0.176)	(0.176)	(0.176)	(0.208)	(0.208)	(0.208)	(0.243)	(0.243)	(0.243)
Constant	11.86***	11.98***	11.84***	13.66***	13.71***	13.56***	20.49***	20.63***	20.40***	16.51***	16.56***	16.22***
	(0.637)	(0.637)	(0.639)	(0.796)	(0.796)	(0.798)	(0.941)	(0.941)	(0.944)	(1.102)	(1.102)	(1.105)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185,337	185,337	185,337	185,337	185,337	185,337	185,337	185,337	185,337	185,337	185,337	185,337
Firms	32,535	32,535	32,535	32,535	32,535	32,535	32,535	32,535	32,535	32,535	32,535	32,535
F	105.7***	105.0***	104.0***	97.75***	96.72***	95.71***						
AIC	1643838	1643793	1643788	1726321	1726317	1726314						
BIC	1644740	1644705	1644710	1727222	1727229	1727235						
Log likelihood	-821830	-821807	-821803	-863072	-863069	-863066						
chi2							12636***	12681***	12693***	9202***	9205***	9222***
u_{it}							9.138	9.139	9.139	10.58	10.58	10.58
ρ							0.201	0.201	0.201	0.155	0.155	0.155

Note: KI stands for knowledge intensity. Reported are coefficients and standard errors in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Models 7 to 12 consider random effects at the firm level. The variance component of the unobserved individual effects (u_{it}) and the proportion of the total variance attributed to the individual component (ρ) are reported at the bottom of Table 2. If ρ is close to zero, the unobserved individual effects are irrelevant for explaining the outcome. While ρ in this case is not very high, the Breusch and Pagan Lagrangian multiplier test suggests that the unobserved individual variance is still substantial. Hence, the random effects estimator is more efficient than pooled OLS. However, random effects assume that the unobserved effects are uncorrelated with other independent variables, which is not necessarily the case. The comparison of the pooled OLS and random effects models provides a crude indication for the extent to which this may be a problem. Fortunately, the random effects models confirm the results of the pooled OLS models. In fact, the relationships turn out to be stronger and more significant for both employment and sales growth. The interaction terms, which are the main interest in this paper, are negative and significant at the 1% level. The turning points for when the total effect of the regional knowledge intensity becomes negative lie at a firm knowledge intensity of 30% and 16% for employment growth and sales growth respectively.

In order to better interpret the interaction terms, Table 3 presents the marginal effects of the regional knowledge intensity on firm employment and sales growth at specific values of firm knowledge intensity while holding all other variables at their mean. The results are very interesting as they show that for firms with low knowledge intensity, the effect of the regional knowledge intensity on firm growth is positive while for firms with high knowledge intensity, this effect turns negative. The negative effect is weakly significant for highly knowledge intense firms as regards employment growth, but strongly significant considering the random effects model for sales growth. Our analysis thus provides strong evidence that knowledge intense firms – in contrast to firms with low in-house knowledge – do not grow faster in knowledge intense regions. Firms with high in-house competencies may even grow more when located outside the main knowledge centres. This is supported in all models.

Table 3 Marginal effects of regional knowledge intensity on employment and sales growth based on OLS and random effects models

at firm	Pooled OLS		Firm random effects	
knowledge	(3)	(6)	(9)	(12)
intensity =	e_growth	s_growth	e_growth	s_growth
0%	0.194***	0.155**	0.293***	0.235***
	(0.0487)	(0.0608)	(0.0713)	(0.0837)
5%	0.162***	0.120**	0.244***	0.160**
	(0.0474)	(0.0593)	(0.0698)	(0.0819)
25%	0.0327	-0.0206	0.0492	-0.138
	(0.0676)	(0.0845)	(0.0928)	(0.110)
50%	-0.128	-0.196	-0.194	-0.512***
	(0.117)	(0.147)	(0.154)	(0.185)
75%	-0.290*	-0.372*	-0.438*	-0.886***
	(0.173)	(0.216)	(0.224)	(0.270)
Observations	185,337	185,337	185,337	185,337
Firms	32,535	32,535	32,535	32,535

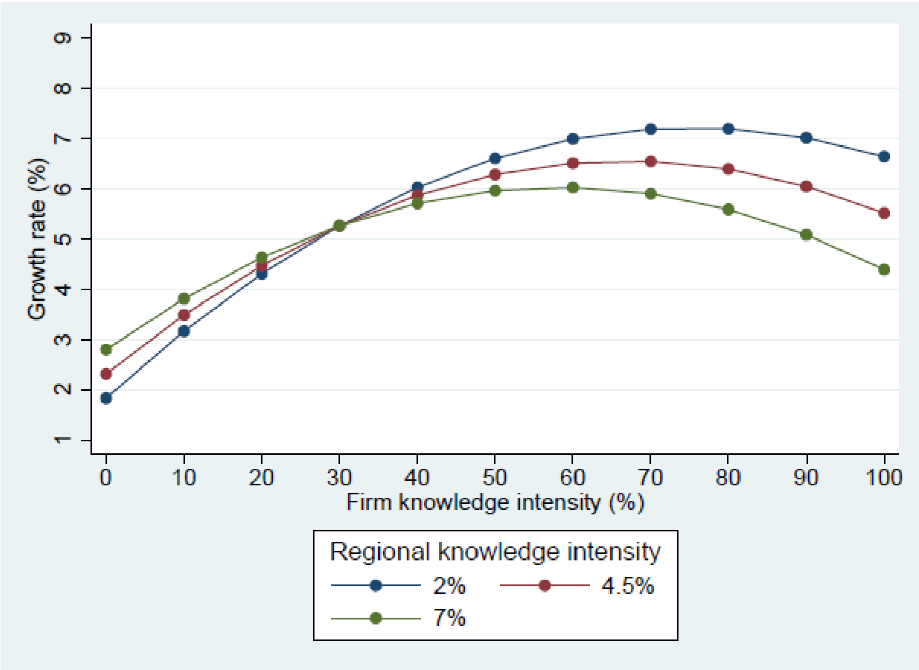
Note: Reported are the marginal effects of regional knowledge intensity at certain levels of firm knowledge intensity while holding the other variables at their mean. Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Figure 1 and Figure 2 illustrate this relationship graphically for employment and sales growth. The x-axis depicts firm knowledge intensity and the y-axis employment growth in Figure 1 and sales growth in Figure 2. The relationships are plotted for different levels of regional knowledge intensity. The figures show a positive but gradually diminishing relationship between firm knowledge intensity and growth. This relationship is stronger, i.e. the slopes are steeper for employment growth than for sales growth. The main interest in this paper, however, is the interplay between firm and regional knowledge intensity. This is why three curves are plotted for firms located in regions characterised by low (2%), medium (4.5%), and high (7%) knowledge intensity. Comparing firms with low in-house knowledge, the figures consistently show that firms tend to grow more if located in knowledge intense regions.

However, for firms with higher knowledge intensity, the positive effect of the region diminishes. At the intersection points of the curves at firm knowledge intensities between approximately 15 and 30%, the regional effect of LKS is estimated to be neural. For firms with higher knowledge intensity, the model even predicts that firms grow more in the periphery, however, at relatively weak statistical significance levels.

Figure 1 Estimated firm employment growth depending on firm and regional knowledge intensities

Pooled OLS (Model 3)



Firm random effects (Model 9)

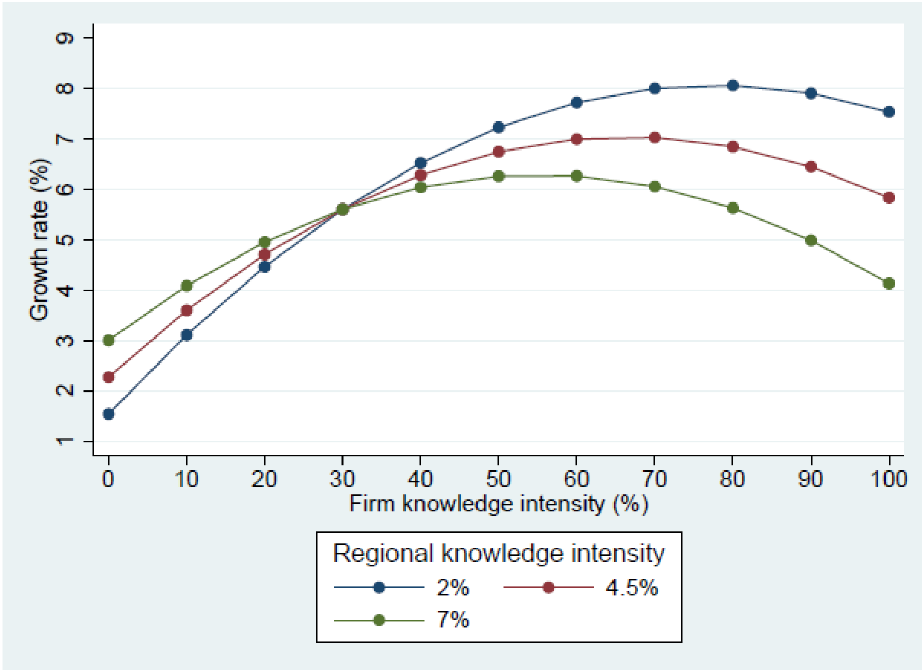
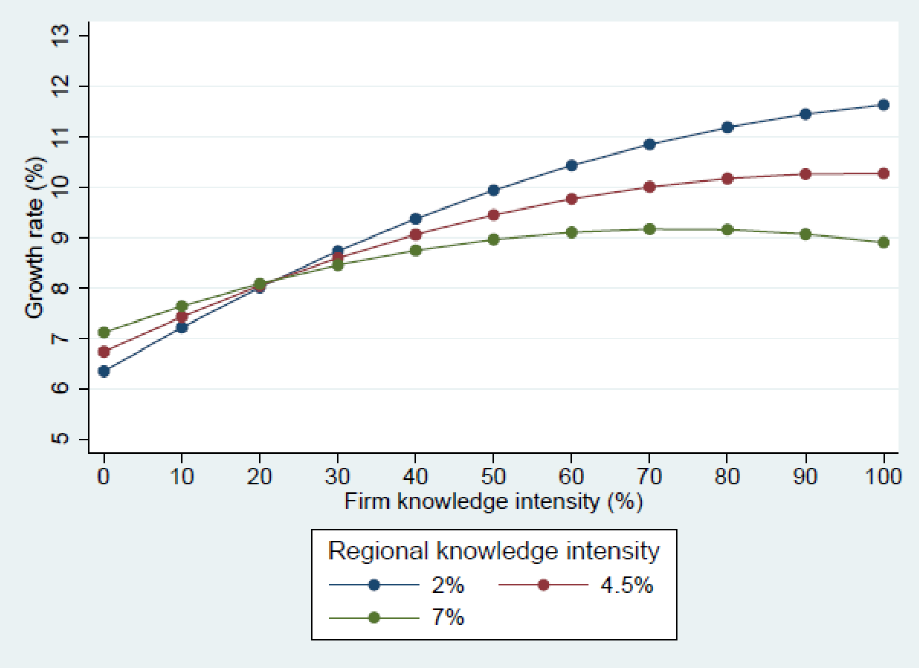
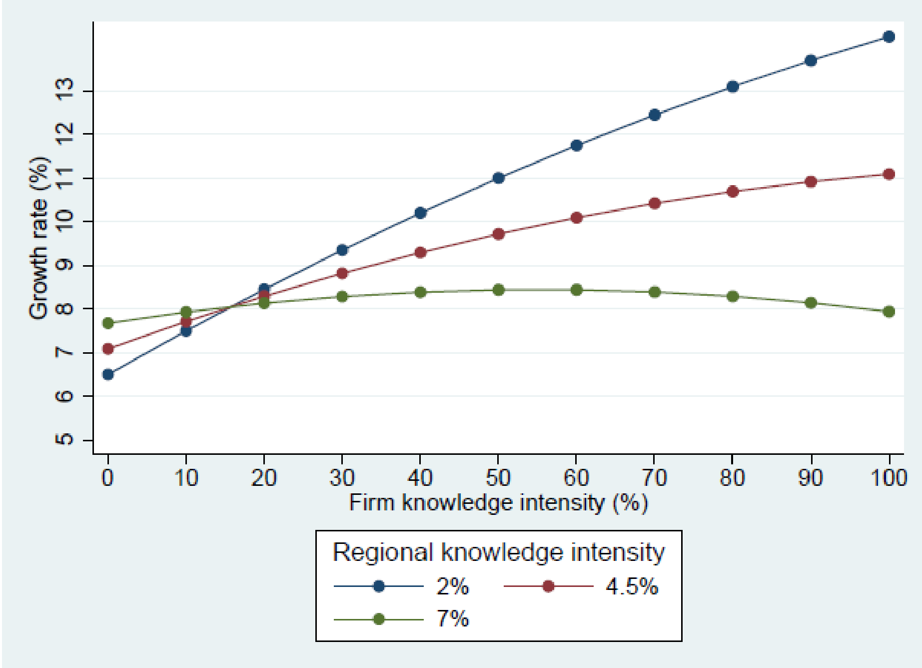


Figure 2 Estimated firm sales growth depending on firm and regional knowledge intensities

Pooled OLS (Model 6)



Firm random effects (Model 12)



5 Robustness tests

In order to check the robustness of the results, the models are estimated with different time-distance decays (λ) and for small, medium and large firms. Annex 2 illustrates the effects of changes to the value of λ. At λ=0.017 the regional knowledge intensities are smoothed out with little municipal variation. The knowledge core regions are Stockholm and surrounding municipalities, Gothenburg and Malmö/Lund. By increasing the distance decay, the regional variety and the differences between individual municipalities increase.

Table 4 presents the robustness tests for employment growth. The findings are robust to changes in the distance decay values. For all reported values, we find that the regional knowledge intensity is positively associated with firm growth if firm knowledge intensity is low. This positive effect, however, diminishes for firms with higher levels of in-house competencies. For firms characterized by very high knowledge intensity, the slope of the regional variable comes out negative but is not significant. The random effects model shows similar patterns even though the relationships are somewhat stronger.

In order to test for robustness to firm size, three size groups were created: small firms from 10 to 49 employees, medium-sized firms from 50 to 249 employees and large firms with 250 or more employees. There are important differences depending on firm size. Small firms with low knowledge intensity grow more in knowledge rich regions. However, for firms with higher knowledge intensity, this effect becomes smaller, eventually negative but not significant. Hence, we find evidence that small firms with high knowledge intensity compensate for a lack of knowledge available regionally to the extent that no growth difference can be identified. Interestingly, for medium-sized firms, we find that there is no significant evidence that firms with low knowledge intensity grow faster in knowledge intensive regions. Medium-sized firms with strong in-house competencies, however, grow more when located in the knowledge periphery. In contrast, large firms show the pattern as commonly expected: Large firms with a high knowledge intensity benefit from regional knowledge intensity, i.e. the positive effects of LKS seem to outweigh the negative ones. While not the main focus of the present paper, the growth patterns for the different firm size groups are highly interesting and warrant further in-depth analysis in future research.

The robustness tests for the regressions on sales growth are presented in Table 5. The results for sales growth are also robust to changes in the distance decay parameter. The negative interaction term, however, is stronger in the random effects model, which is why the effect of regional knowledge intensity turns negative and significant for firms with high internal knowledge. As regards firm size, we find that small firms with low in-house knowledge grow faster in the knowledge centers, which is not the case for firms with high internal knowledge. The results are not significant for medium-sized and large firms.

In summary, the robustness tests confirm our results. The results are highly robust for different distance decay parameters and valid for small and medium-sized firms. The prevailing positive effects of LKS are only visible for firms with low internal knowledge (except for large firms). In contrast, the positive and negative effects of LKS neutralize for firms with high knowledge intensity, and there is even some evidence that the negative ones dominate. For sales growth this pattern holds for small firms. The results do not hold for large firms, however. Large firms characterized by high knowledge intensity exhibit a higher employment growth in the knowledge centers.

Table 4 Robustness test for employment growth with different values for λ and different firm sizes

at firm	Pooled OLS						Firm random effects					
knowledge	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
intensity =	$^3\lambda$ = 0.025	$^3\lambda$ = 0.050	$^3\lambda$ = 0.100	10-49	50-249	250+	$^3\lambda$ = 0.025	$^3\lambda$ = 0.050	$^3\lambda$ = 0.100	10-49	50-249	250+
0%	0.169***	0.127***	0.115***	0.149***	0.0832	0.472**	0.246***	0.185***	0.170***	0.177**	0.0905	0.652**
	(0.0405)	(0.0312)	(0.0261)	(0.0538)	(0.113)	(0.222)	(0.0593)	(0.0458)	(0.0381)	(0.0777)	(0.159)	(0.317)
5%	0.142***	0.108***	0.103***	0.136***	0.0117	0.499**	0.205***	0.157***	0.151***	0.167**	0.0115	0.751**
	(0.0397)	(0.0309)	(0.0257)	(0.0526)	(0.109)	(0.211)	(0.0583)	(0.0452)	(0.0376)	(0.0762)	(0.154)	(0.306)
25%	0.0308	0.0280	0.0559	0.0850	-0.274*	0.607**	0.0426	0.0420	0.0759	0.125	-0.305	1.149***
	(0.0580)	(0.0467)	(0.0392)	(0.0752)	(0.154)	(0.301)	(0.0798)	(0.0642)	(0.0538)	(0.102)	(0.204)	(0.400)
50%	-0.108	-0.0714	-0.00306	0.0215	-0.631**	0.742	-0.161	-0.101	-0.0178	0.0729	-0.700**	1.647**
	(0.101)	(0.0819)	(0.0690)	(0.130)	(0.270)	(0.542)	(0.133)	(0.109)	(0.0921)	(0.168)	(0.343)	(0.678)
75%	-0.246*	-0.171	-0.0621	-0.0420	-0.989**	0.877	-0.364*	-0.244	-0.111	0.0207	-1.095**	2.144**
	(0.149)	(0.121)	(0.102)	(0.192)	(0.400)	(0.813)	(0.194)	(0.159)	(0.135)	(0.245)	(0.503)	(1.000)
Observation	185,337	185,337	185,337	154,277	26,008	5,052	185,337	185,337	185,337	154,277	26,008	5,052
Firms	32,535	32,535	32,535	26.008	4,350	813	32,535	32,535	32,535	26.008	4,350	813

Note: Reported are the marginal effects of regional knowledge intensity at certain levels of firm knowledge intensity while holding the other variables at their mean. Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

Table 5 Robustness test for sales growth with different values for λ and different firm sizes

at firm knowledge intensity =	Pooled OLS						Firm random effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$^{3}\lambda = 0.025$	$^{3}\lambda = 0.050$	$^{3}\lambda = 0.100$	10-49	50-249	250+	$^{3}\lambda = 0.025$	$^{3}\lambda = 0.050$	$^{3}\lambda = 0.100$	10-49	50-249	250+
0%	0.126**	0.0938**	0.0943***	0.167**	-0.0366	0.178	0.188***	0.137**	0.127***	0.245***	-0.0477	0.155
	(0.0506)	(0.0390)	(0.0326)	(0.0673)	(0.160)	(0.302)	(0.0697)	(0.0537)	(0.0448)	(0.0931)	(0.202)	(0.391)
5%	0.100**	0.0784**	0.0859***	0.140**	-0.0718	0.113	0.129*	0.0975*	0.101**	0.177*	-0.0967	0.136
	(0.0496)	(0.0386)	(0.0321)	(0.0658)	(0.154)	(0.287)	(0.0684)	(0.0531)	(0.0441)	(0.0912)	(0.195)	(0.375)
25%	-0.00192	0.0168	0.0525	0.0340	-0.212	-0.145	-0.104	-0.0600	-0.00561	-0.0956	-0.292	0.0613
	(0.0725)	(0.0584)	(0.0489)	(0.0940)	(0.217)	(0.408)	(0.0950)	(0.0765)	(0.0641)	(0.123)	(0.264)	(0.505)
50%	-0.130	-0.0601	0.0106	-0.0990	-0.388	-0.468	-0.396**	-0.257**	-0.139	-0.436**	-0.537	-0.0321
	(0.126)	(0.102)	(0.0862)	(0.163)	(0.380)	(0.736)	(0.160)	(0.131)	(0.111)	(0.206)	(0.453)	(0.877)
75%	-0.257	-0.137	-0.0312	-0.232	-0.564	-0.791	-0.688***	-0.454**	-0.272*	-0.777***	-0.782	-0.126
	(0.186)	(0.151)	(0.127)	(0.240)	(0.564)	(1.103)	(0.234)	(0.191)	(0.162)	(0.300)	(0.669)	(1.302)
Observation	185,337	185,337	185,337	154,277	26,008	5,052	185,337	185,337	185,337	154,277	26,008	5,052
Firms	32,535	32,535	32,535	26.008	4,350	813	32,535	32,535	32,535	26.008	4,350	813

Note: Reported are the marginal effects of regional knowledge intensity at certain levels of firm knowledge intensity while holding the other variables at their mean. Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.

6 Discussion and conclusion

This paper addresses one of the fundamental propositions in modern economic geography: that knowledge dynamics largely drive the clustering of economic activities in space (MALMBERG and MASKELL, 2002). The dominant view holds that in particular firms with high-levels of in-house knowledge should benefit from a location in regions with a rich knowledge infrastructure (HEALY and MORGAN, 2012; SHEARMUR, 2012). This would then imply an upward spiral for knowledge intensive firms in knowledge intensive regions while knowledge intensive firms in the knowledge periphery should lose ground. In the wider context of a learning or knowledge economy (LUNDVALL and JOHNSON, 1994; COOKE and LEYDESDORFF, 2006), where knowledge is essential for the competitiveness of firms and regions, this would also suggest an increasing divergence between the knowledge core and periphery.

Following this knowledge-based theory of spatial clustering, regions with low knowledge intensity face nearly insurmountable difficulties. In this paper, we put forward a more nuanced view suggesting that knowledge intensive firms in the knowledge periphery may prosper because i) they are less dependent on LKS and are more able to source knowledge at other scales (GRILLITSCH and NILSSON, 2015; JAKOBSEN and LORENTZEN, 2015), and ii) they are less likely to suffer negative knowledge spillovers to closely located competitors (SHAVER and FLYER, 2000; ALCÁCER, 2006; MARIOTTI et al., 2010; ANGELI et al., 2013).

The empirical study supports the more nuanced perspective advanced in this paper. While we find that the level of regional knowledge intensity is positively related to firm growth overall, we find no evidence that knowledge intensive firms grow faster in knowledge rich regions. In contrast to the largely presumed synergy effect between firm internal and regional knowledge intensity, our study provides strong evidence for a negative relationship between the two.

One interpretation of this is that negative knowledge externalities, e.g. knowledge leakage and labor poaching, are especially prevalent in knowledge dense regions, and that these negative externalities do indeed, as argued by some previous studies, mainly affect strong firms (ALSLEBEN, 2005; ALCÁCER and CHUNG, 2007; ANGELI et al., 2013). It appears that for these firms the negative knowledge externalities may outweigh the positive externalities associated with the inflow of knowledge and skilled labor (cf. COMBES and DURANTON, 2006; MARIOTTI et al., 2010). Because knowledge intensive firms also have a greater ability to compensate for a lack of LKS by building knowledge pipelines with distanciated partners the combined effect of firm and regional level knowledge becomes negative. These findings thus go against what can be expected from much of the literature in economic geography where knowledge based agglomeration economies are argued to mainly benefit knowledge intensive firms.

As for firms with low internal knowledge, our findings support research that posits that weaker firms (in terms of internal knowledge endowments) have more to gain from LKS than stronger firms (e.g. SHAVER and FLYER, 2000). The reason for this is arguably twofold: Firstly, weak firms are relatively less affected by negative knowledge externalities in the form of knowledge leakage and labor poaching. Secondly, it is relatively easier to access knowledge spillovers from local actors as compared to initiating and building distanciated pipelines for knowledge exchange. Despite having lower absorptive capacity, the combined effect from location in knowledge dense regions is therefore positive for firms with weak internal knowledge base.

Coming back to the debate on knowledge core and peripheral regions, this study implies that growth differences at the level of the firm can largely be overcome if firms succeed in building a strong internal knowledge base and absorptive capacity. Especially because, as noted in previous studies (TÖDTLING and TRIPPL, 2005; FITJAR and RODRÍGUEZ-POSE, 2011), extra-regional knowledge sources play a central role for the innovativeness and competitiveness of firms in the periphery. Again, it is the firms with a high absorptive capacity who are best equipped to use extra-regional collaborations to compensate for a lack of knowledge available regionally (GRILLITSCH and NILSSON, 2015).

Limitations and directions for future research

The aim of this study is to investigate whether knowledge intensive firms benefit more from location in knowledge dense regions than firms with low knowledge intensity by analyzing the interaction effect of firm internal knowledge and LKS related to firm growth. While this approach enables the study of a large set of firms over time, we do not explain how some firms in the periphery succeed in maintaining high levels of knowledge and how they can overcome geographical distance to knowledge sources and engage in extra-regional networks; i.e. the causal mechanisms behind the patterns.

Also, from a broader regional growth perspective, the paper focuses on the performance of individual firms and does not include other mechanisms such as the role of spin-offs and new firm formation, which can be expected to contribute more to regional growth within agglomerations than in peripheral regions.

Our study suggests that the effect of location in knowledge dense regions varies between different types of firms. In addition to firm knowledge intensity, other dimensions such as firm size, industry and firm level routines may be relevant. In fact, the results of our robustness tests point to important and highly interesting differences between firms of different sizes. This warrant further in-depth analysis in the future.

The findings presented above are derived from a study of Swedish data. While our discussion identifies plausible causal relationships that are broadly applicable across empirical settings, the findings are primarily applicable to other advanced open market economies. In economies that are primarily built on natural resources external economies are less derived from knowledge-based dynamic externalities (cf. MALMBERG et al., 1996). Similarly, the existence of a well-developed infrastructure is arguably a precondition for analyzing the interrelationship of core and periphery in terms of knowledge flows and firm performance. Because of this, Sweden is a good context in which to conduct our study as it comprises both knowledge dense regions and knowledge peripheries located far apart but connected with well-developed infrastructure.

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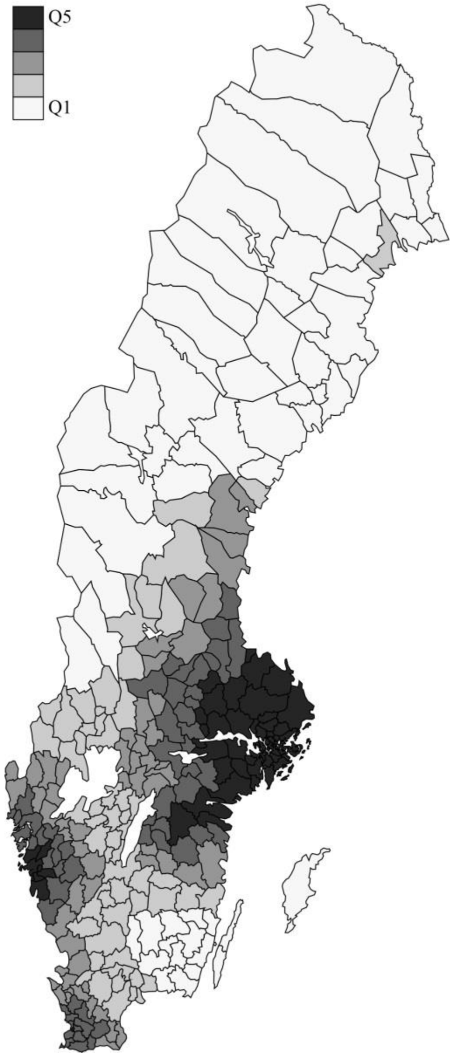
Annex 1: Correlations

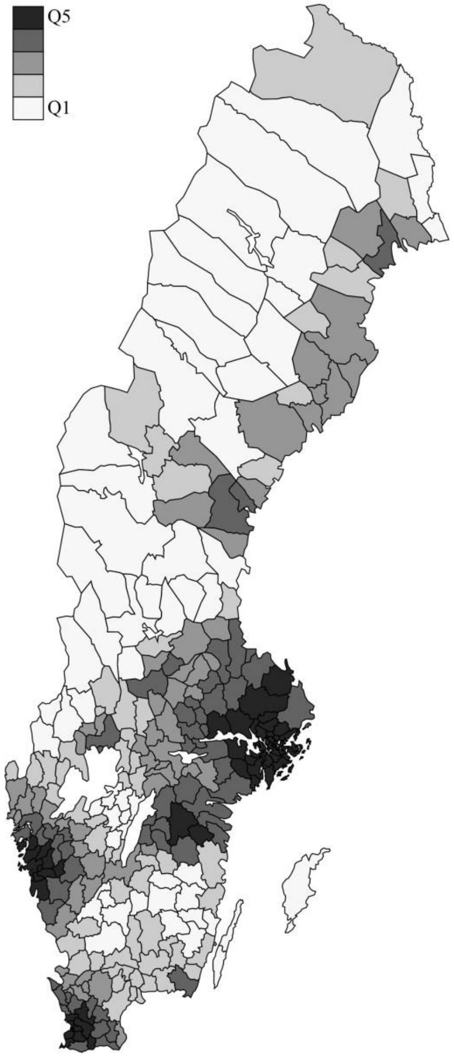
Variables		1	2	3	4	5	6	7	8
1	Employment growth (%)	1.0000							
2	Sales growth (%)	0.3658	1.0000						
3	Regional knowledge intensity (%)	-0.0012	-0.0153	1.0000					
4	Firm knowledge intensity (%)	0.0450	0.0373	0.1652	1.0000				
5	Finance (%)	0.0058	-0.0104	-0.0252	-0.0210	1.0000			
6	Investments	0.0173	0.0100	-0.0133	0.0092	0.0101	1.0000		
7	Metropolitan area (dummy)	0.0332	0.0231	0.5582	0.1897	-0.0196	-0.0107	1.0000	
8	Number of employees (log)	-0.1442	-0.0606	0.0611	0.0557	0.0010	0.0158	0.0541	1.0000

Annex 2: Regional knowledge intensities for different values of λ

λ=0.017



λ=0.050



λ=0.100