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Industry-specific firm growth and agglomeration

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Abstract:

This paper studies the industry-specific relationship between industrial clustering and firm growth. Micro- This paper geographically defined agglomeration measures, free of the modifiable areal unit problem (MAUP), are used to study 23 industries. The spatial impacts of agglomeration of related economic and knowledge generating activities are examined by using travel time distances, a flexible log-logistic decay function framework and quantile regression techniques. We find that firms' growth prospects tend to be hampered by the agglomeration of own-industry employment, but improved by proximate scientific activity. Results depend on the kind and age of industry. Furthermore, the optimal decay functions that measure agglomeration effects considerably vary both between the industries and variables. Three illustrative cases of industries are discussed in more details.

Keywords: Firm growth, industrial clusters, agglomeration, MAUP, distance decay function, quantile regression.

JEL Classifications: C31, D92, L25, R11

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1 Introduction

The geographical location has for a long time been "a neglected determinant of firm growth" (AUDRETSCH and DOHSE 2007), but recently an increasing bulk of literature examines the impact of being located within agglomerations and industrial clusters or in proximity to universities on the performance of firms. However, empirical findings are still contradictory. This is not surprising, as one of the few invariables of industrial dynamics is the heterogeneity of firms (DOSI et al. 2010). From the existing literature, four key issues are known as a potential source of contradicting results: first, there are strong differences between industries. For instance, agglomeration economies differ between manufacturing and service industries as well as at finer levels of disaggregation (e.g., BEAUDRY and SWANN 2009). Second, processes and mechanisms differ with the industry's age and particularly its stage in the industrial life-cycle. Empirical investigations suggest that agglomeration is more important in the initial phase of an industry while it might become even harmful when the industry is more established (e.g., POTTER and WATTS 2011). Third, agglomeration can be measured with different statistical methods and fourthly, the spatial dimension used within the methods matters. Results might depend on the chosen regional level, i.e. if the investigation is done on the city-level, zip-codes, or other functionally definitions of regions. Some investigations even report contradicting results using the same dataset when changing from one aggregation level to another (e.g., BUERGER et al. 2010).

Recently, much effort has been undertaken to improve the understanding of spatial dependencies by shifting from aggregated large-scale investigations to more micro-geographic data driven approaches (e.g. DURANTON and OVERMAN 2005). Beside the issue of availability, micro-geographic data also requires new techniques in order to integrate them into econometric models. Given the few existing publications that deal with micro-geographic data, the literature remains quite unclear on how the methodological challenges can be met. While micro-geographic data enhances the validity of research findings on spatial matters of firm growth, investigations have yet mostly neglected the physical nature of firm's geographic location. As regards the access to growth relevant sources of agglomeration economies, its location relative to the road network plays an important role.

Given these yet unresolved questions, the aim of this paper is to re-examine the effects of external factors to firm growth at a disaggregated level of industries and at a micro-geographical scale which makes the choice of the appropriate regional level obsolete. This is achieved by geolocating firms into space and by calculating travel time distances to all related economic and knowledge generating activities. Firms' access to these activities is spatially discounted by a flexible log-logistic distance decay function, which can be deduced from behavioural assumptions and which is further specified based on empirical data. Using a quantile regression framework, the impact of nearby economic and knowledge generating activities on employment growth of German firms is compared across 23 industries, that is groups of related industries as defined by the EU Cluster Observatory. The findings suggest that being located in agglomerations of own-industry employment does not increase but rather reduces firms' growth prospects. In contrast hereto, being located in proximity to knowledge generating activities tends to be positively related to firm growth, although the spatial scale of what means proximity varies across industries. In order to account for the heterogeneity of the analysed industries, results from three representative cases are finally discussed more in-depth.

The paper is structured as follows. In the second section, expectations on the industry-specific impacts of nearby economic and knowledge generating activities on firm growth are deduced from the existing literature. Data issues are described in the third section, while the methodology of a data-driven distance decay function specification and a quantile regression framework with spatially discounted variables is outlined in the fourth section. Section five presents and discusses the results. Section six concludes.

2 Literature

2.1 The impact of agglomeration on firm growth

The economic literature has studied firm growth extensively from different point of views. Mostly by augmenting a Gibrat-like growth regression, variables such as the firm's age, its strategy or its location in space have been analysed. Concerning the latter aspect, a rich body of academic work exists that can be labelled with the term 'agglomeration theory', among whom the theory of industrial clusters (PORTER 2000), which comprises being located in spatial proximity to similar firms and associated institutes like universities, has attracted high interest both in science and politics. While still acknowledging the positive influence of clusters on spin-offs, FRENKEN et al. (2011: 2) conclude in their survey on *industrial dynamics and economic geography* that "there is little evidence that clusters enhance firm growth and survival". Various empirical investigations show that industrial clusters contribute to firm growth only under certain circumstances and that it is of high importance which constituent parts (agglomeration of similar firms, research institutions etc.) are observed. The comprehensive study of BEAUDRY and SWANN (2009) on 56 two-digit industries in the UK suggests that local employment in the same sector has often only positive effects for manufacturing industries but negative effects for service industries. Besides the kind of industry, the industry's age and its life-cycle stage can help to understand the multifaceted influences of industrial clusters on firm growth (FELDMAN 1999). This is also reflected by the recent focus on cluster life-cycles in general (as manifested by a special issue in Regional Studies edited by BOSCHMA and FORNAHL 2011), and on the dynamics of agglomeration economies during such life-cycles in particular (e.g., NEFFKE et al. 2011). In the early phases of industry life-cycles, which often coincidence with cluster life-cycles, the rates of start-ups and spin-offs tend to be high. Local conditions, like the presence of related industries, play a major role in the initial development of clusters. At more mature stages, however, market growth slows down and a kind of equilibrium is reached (BRENNER and SCHLUMP 2011). Empirical evidence suggests that under these circumstances, firms do not benefit anymore from being located in agglomerations (AUDRETSCH and FELDMAN 1996), and their growth prospects might be even hampered due to increasingly prevailing negative agglomeration economies such as intensified competition (POTTER and WATTS 2011).

The explanation of why firms might benefit from industrial clusters has shifted to phenomena like innovation, learning and knowledge spillovers (MALMBERG et al. 2000). Growth relevant knowledge is generated by competing and cooperating firms, but also by research activities in universities or R&D institutes. In the latter case, the literature is less ambiguous. Many studies show a positive link between the presence of universities and firms' innovation (e.g., JAFFE 1989) and growth performance (e.g., AUDRETSCH and LEHMANN 2005, CASSIA et al. 2009 or RASPE and VANOORT 2011). This relates to research on the relationship between regional knowledge intensity and firm performance, which (indirectly) assumes spatially bounded knowledge spillovers to be one of the main mechanisms of agglomeration economies (FRENKEN et al. 2011).

To conclude, we expect that industrial clusters have manifold effects on firm growth: effects of the agglomeration of related economic activities are ambiguous with a tendency towards negative effects, depending on the kind of industry and its stage in the industry life-cycle. In contrast, the effects of proximate knowledge generating activities should be rather positive.

2.2 Spatial matters of firm growth and agglomeration

Although the impact of industrial clusters on firm growth is highlighted in many studies, the literature has remained quite silent on the spatial range of their influence and the actual definition of space. For most of the papers, the definition of space arises from the used dataset, i.e. the spatial aggregation level of the data such as cities or regions. For quantitative driven investigations, mostly regression models, this spatial definition concerns both the dependent and the independent variable.

Table 1: Literature overview

Approach	Observation	Industry-focus	MAUP	Examples
Macro (regions)	Intra-region effects	No	Yes	FRENKEN et al. 2007
		Comparison		GLAESER et al. 1992; HENDERSON et al. 1995; PORTER 2003 SPENCER et al. 2010
	Neighborhood effects	No		KUBIS et al. 2009; DELGADO et al. 2010; ARTIS et al. 2011
		Comparison		DELGADO et al. 2012
Micro (firms or plants)	Intra-region effects	No	Yes	GUISO and SCHIVARDI 2007; CAINELLI 2008; BOSCHMA et al. 2009; CASSIA et al. 2009; ANDERSSON and LÖÖF 2011
		Comparison		RIGBY and ESSLETZBICHLER 2002; HENDERSON 2003; AUDRETSCH and DOHSE 2007; BEAUDRY and SWANN 2009; WENNBERG and LINDQVIST 2010
	Distance bands	No	No	HOOGSTRA and VANDIJK 2004; BALDWIN et al. 2008; ERIKSSON 2011
		Comparison		ROSENTHAL and STRANGE 2003; BALDWIN et al. 2010; GRAHAM 2009
	Distance decay	No		AUDRETSCH and LEHMANN 2005; LYCHAGIN et al. 2010
		Comparison		VANSOEST et al. 2006; GRAHAM et al. 2010; DRUCKER and FESER 2012; DRUCKER 2012

Table 1 provides a non-exhaustive overview on the different approaches that can be found in the literature. Starting with the dependent variable, two general concepts can be separated: The macro approach investigates growth effects on a regional level while the micro approach deals with growth effects on single firms. Empirical evidence exists that the clustering of industries exerts a positive impact on regional economic performance, both for the entire regional economy (e.g., DELGADO et al. 2010) as well as at the disaggregate level of industries within the region (e.g., DELGADO et al. 2012). This evidence is refined by the insight that the underlying mechanisms like knowledge spillovers are most pronounced in regions where at the same time the variety and the relatedness of the agglomerated industries are highest (FRENKEN et al. 2007). Spatially more sophisticated approaches deal with neighbourhood effects – how neighbouring regions influence the growth of a specific region. However, recently both the growing access to firm data and to computational power, have led to a focus on micro approaches. Investigating growth on the firm level allows for a more sophisticated testing as firm-specific variables can be included and inner-regional heterogeneity can be observed. While the dependent variable of the micro approach is the growth rate of a single firm and therefore not aggregated, most studies explain growth processes by means of characteristics of the region the firm is located in. Here, the literature has brought forward manifold regional measures for concentration, diversity or competition, ranging from simple counts, relative measures like the LQ to more complex, derivate measures. Because imperfect competition and heterogeneous firms are defining characteristics of the economic landscape, regions as consistent and homogenous aggregates are impossible to exist. As a consequence, regionalization, an ex-post abstraction of the continuous landscape, would imply a huge loss of information (for an extensive discussion on this issue we refer to PINSKE and SLADE 2010 or HARRIS 2011). Thus, analogue to the macro approaches, results are affected by the arbitrariness of regional boundaries and moreover by the chosen level of aggregation. This issue of zoning and scaling was first described by OPENSHAW (1984) and coined with the term Modifiable Areal Unit Problem (MAUP). By varying the spatial scale of analysis, BUERGER et al. (2010) as well as WENNBERG and LINDQVIST (2010) show empirically that the MAUP is highly relevant for agglomeration economies.

Avoiding the MAUP requires two methodological aspects: First, the aggregation level of the data should be as low as possible. DURANTON and OVERMAN (2005) refer to this as micro-geographic data, which we obtain in our case by computing the easting and northing of each firm's municipality. Municipalities represent the lowest aggregation level in Germany, currently with a number of 11249 and an average size of 31.6 km^2. Second, distance-based methods have to be applied for the calculation of the independent variables. One method is using distance bands, i.e. counting the observance of firms at specific radii (e.g., ROSENTHAL and STRANGE 2003). Another approach is the use of distance decay functions that build proxy values of agglomeration by summing up localizable activities multiplied by inverted distances. Various specifications of both the distance bands and the decay functions exist in the literature. Concerning the latter approach, mostly simple linear (e.g., AUDRETSCH and LEHMAN 2005) or exponential decay functions (e.g., DRUCKER and FESER 2012) are used, although DEVRIES et al. (2009) have shown that a log-logistic function is best suited for modelling spatial interactions, in their case, the effect of transportation costs on commuting flows. This function, derivable from behavioural assumptions, represents a rather flexible approach, to which the exponential decay and even the distance bands are only special cases. Because agglomeration economies are reported for a wide range of different distances, from a narrow local to supra-regional scale, in our approach the best fitting decay function will be identified based on empirical data and for each industry separately.

Beside the choice of the distance model, results may also depend on the way how distance between firms is computed. The vast majority of distance based investigations uses orthodromic distances (e.g. km or miles), although this might cause errors if the 'economic' distance between firms deviates from the orthodromic distance, for instance if firms are located in mountainous or less well connected regions (DURANTON and OVERMAN 2005). Obviously, driving distance or travel time are more appropriate, given that agglomeration economies are assumed to arise from low transportation costs or the convenience of face-to-face contacts. One of the few exceptions using travel times is the work of AUDRETSCH and LEH-

MANN (2005), where the growth of firms is investigated with respect to the firms' driving distance to the their closest university. However, studies where driving distances are computed to thousands of locations are, due to the high computational costs of route planning, very rare. Using an efficient many-to-many route planning algorithm, introduced by KNOPP et al. (2007), we compute travel times between all German municipalities, allowing us to investigate agglomeration effects on firm growth from a more realistic spatial perspective.

With respect to the discussed literature, the paper at hand belongs to the group of micro approaches as it observes the growth rates of each individual firm. It uses a flexible distance decay function and compares agglomeration effects across disaggregated industries. From a methodological point of view, our paper differs from the existing literature regarding two aspects: First, instead of spherical distances travel time in minutes is used. Secondly, we do not anticipate a specific distance decay function but include its optimization into our analysis in order to detect possible differences among industries.

3 Data

3.1 Definition of industries

The 23 industries used for the current analyses were taken from the EU Cluster Observatory and can be seen as a standard definition for industry-related policy programmes on regional development in Europe. The definition goes back to a US cluster mapping project undertaken by PORTER in the early 2000s and is based on the distinction between local and natural-resource-driven industries on the one hand, and export-oriented traded industries on the other (PORTER 2003). The latter industries were grouped according to co-location patterns within the standard industrial classification data across the US and led to groups of related industries, also known as industrial clusters. PORTER’s analysis concludes that the regional presence of those clusters can be seen as a driver for regional economic performance and the positive development of embedded firms (PORTER 2003, WENNBERG and LINDQVIST 2010). This makes it a suitable definition to survey the relationship between industrial clustering and firm growth.

3.2 Dependent variable

The BvD Amadeus database discloses the address of the firms’ headquarter location. As operational and strategic decisions are often made within this organizational unit, their regional environment will be most decisive in affecting growth prospects (BEAUDRY and SWANN 2009). This rationale breaks down for larger firms, which tend to be less focused on their headquarters, but disperse activities in many increasingly independent establishments across the country and even beyond. Therefore, the analysis is restricted to firms with no more than an annual average of 1000 employees. Also very small firms with less than 5 employees, which growth processes are known to be rather erratic, are excluded (COAD 2009).

Growth rates are calculated by taking the difference of the natural logarithms of the size *S* (measured by employment) of firm *i* between two successive years *t*:

$$g_{i,t} = \log(S_{i,t+1}) - \log(S_{i,t}) \tag{1}$$

Confronted with an unbalanced panel from 2004 to 2010, yearly growth rates are pooled together. In the course of one year, firms essentially face three options: they may expand, shrink or remain at the previous level. Zero-growth events, in particular quite abundant for employment, make up 44.5% of the original data. A considerable but unknown share of these events can be attributed to a lack of regular updating of database entries, which are simply extrapolated from previous years. Including these events would bias the assessment of the impact of agglomeration on firm growth. Besides this data issue, firms that opt for the option not to grow might be distinct from actually changing (expanding or shrinking) firms. Although being an economically rational choice in the absence of any changes in business opportunities, this option is often preferred even in cases when opportunities have changed. To name just a few examples, firms might be reluctant to expand because the inclusion of new employees is costly as it implies re-organisation of internal tasks and management functions, or the fear of losing control might frighten some managers (COAD 2009). In a similar vein, firms can be reluctant to shrink despite reduced business opportunities. Firms invest in building up redundancies in difficult times instead of immediately dissolving existing working contracts, or managers might be not fully aware of the necessary down-sizing. Because from a technical point of view it is impossible to distinguish between data problems and the various other reasons why firms do not grow, we analyse only growth events in which the size of firms actually changes.

Industries with less than 1000 yearly growth events are omitted due to robustness issues. The remaining 23 industries are listed in table 2, together with their number of pooled growth events $g_{i,t}$, number of firms, and the average age of these firms.

Table 2: Overview on analysed industries

ID	Name	N ($g_{i,t}$)	N (firms)	Age
1	Agricultural products	1077	688	19
2	Automotive	1721	632	20
3	Building fixtures & equip.	2529	1115	23
4	Business services	5057	2417	13
5	Chemical products	1385	504	24
6	Construction	6278	3057	24
7	Distribution	5108	2488	22
8	Entertainment	1179	558	14
9	Financial services	1108	540	14
10	Heavy Machinery	1041	391	21
11	Instruments	1336	539	25
12	IT	2668	1161	15
13	Media & publishing	3038	1654	23
14	Medical devices	1068	573	19
15	Metal manufacturing	7189	3265	25
16	Paper products	2159	970	24
17	Plastics	1861	748	24
18	Processed food	4652	2222	26
19	Production technology	5273	2072	24
20	Telecom	1406	524	21
21	Textiles	1097	488	26
22	Tourism & hospitality	2100	1472	18
23	Transportation & logistics	2406	1013	17

3.3 Independent variables

Firms' potential to benefit from industrial clusters is specific to characteristics of firms as well as of the corresponding regions (BEUGELSDIJK 2007; ERIKSSON 2011). Therefore, the independent variables consist of three different kinds: First, we control for relevant demographic properties of the firms. Second, we include measures of the general environment of the region the firm is located in. Third, the focus of this paper lies on firm-specific location variables reflecting economic agglomeration and scientific activity.

Control variables: demographic and regional variables

Building upon the literature on firm growth, which mostly extends a Gibrat-like growth regression (see Coad 2009 for an overview), we control for the logarithm of size, age, and whether or not it is a subsidiary firm. It counts as a stylized fact in industrial dynamics that firm growth is negatively related to both size and age. In addition, two variables are chosen to control for the general regional environment. Urbanization economies *per se*, which are rather independent from the surrounding industrial structure (BUERGER et al. 2012) and which might be both positive or negative, can be measured by the population density of the corresponding district, wherein a firm is located (ERIKSSON 2011).[1] The unemployment rate of the firm's regional labour market reflects the vitality of the regions' socio-economic conditions. In the special case of Germany it also accounts for structural differences along the east-west and north-south divide. Data for both variables is obtained from the German Federal Statistical Office. The global macroeconomic recession 2008-10 systematically lowered the firms' growth prospects. Therefore, a dummy variable for growth events of the crisis years is constructed. Finally, the absolute location within Germany might influence the magnitude of agglomeration economies. Potential cross-border effects cannot be considered, which discriminates firms located close to the border. Due to historical reasons, two dummies are constructed: one for the location in border regions with the New Member States of the EU and one for all other border regions.

Firm-specific location variables: own-industry employment and publications

In contrast to the regional control variables that account for a rather diffuse socio-economic environment (or "social filter", as denominated by RODRÍGUEZ-POSE and CRESCENZI 2008), other economic and knowledge generating activities can be traced back to concrete localizations in space: firms compete, cooperate, and learn from each other, and new scientific knowledge originates from universities and research institutes. These economic or knowledge generating activities can be approximated by the number of employees in the same industry and scientific publications, respectively. The Federal Employment Agency provides data on industry-specific employment for municipalities, the lowest aggregation level in Germany. Data on scientific publications were collected from the ISI Web of Science and assigned to municipalities on basis of authors' addresses. The subsequent section explains how firm-specific location variables can be constructed by discounting these geo-localized activities with their distances to the firm's location. Therefore, bilateral travel times are calculated by exploiting results from graph theory and data on the German road network from the OpenStreetMap project; the algorithms are described in DUSCHL et al. (2011) and more extensively in GEISBERGER et al. (2010). Intra-municipality distances are set to 5.01 minutes, the average bilateral travel time between 1000 randomly drawn pairs of firms' address locations, each belonging to the same municipality.

4 Model and estimation

4.1 Construction of firm-specific location variables

Employees in the same industry and scientific publications are discounted by an industry-specific distance decay function $f(d_{im})$ based on travel time distances d_{im} between the places of firms i and the municipalities m. The firm-specific variables for agglomeration of related economic (*AGGL*) and knowledge generating activities (*KNOW*), after normalizing with $\mu_{AGGL} = \frac{\sum_m empl_{m,t}}{\sum_i \sum_m f(d_{im}) empl_{m,t}}$ and $\mu_{KNOW} = \frac{\sum_m publ_{m,t}}{\sum_i \sum_m f(d_{im}) publ_{m,t}}$, read:

$$
\begin{aligned}
AGGL_{i,t} &= \mu_{AGGL} \sum\nolimits_m f(d_{im})\, empl_{m,t} \\
KNOW_{i,t} &= \mu_{KNOW} \sum\nolimits_m f(d_{im})\, publ_{m,t}
\end{aligned}
\tag{2}
$$

These spatially discounted variables can be included in a simple linear model (for spatial econometric issues we refer to ANDERSSON and GRASJÖ 2009)[2]

$$
g_{i,t} = \alpha + \beta_1 AGGL_{i,t} + \beta_2 KNOW_{i,t} + \sum\nolimits_{j=3}^{10} \beta_j x_{i,t,j} + \varepsilon_{i,t} \tag{3}
$$

with α and β representing the coefficients to be estimated and x the seven firm- and region-specific control variables. The error term is denoted by $\varepsilon_{i,t}$. The applied normalization procedure allows for an interpretation of the corresponding regression coefficients as the impact of one additional employee or publication on the growth of a firm with a given distance. After briefly introducing quantile regression techniques as an adequate estimation method in the context of firm growth, the still outstanding specification of the distance decay function $f(d)$ will be discussed.

4.2 Estimation using quantile regression techniques

It is one of the stylized facts of industrial dynamics that firm growth rates are not normally distributed, but show fat tails (for an overview on empirical studies for different countries see COAD *forthcoming*). Therefore, quantile regression techniques, which are robust to outliers in the dependent variable and free from any distributional assumption in the error term (BUCHINSKY 1998), are more appropriate. Besides, the specific conditional quantiles of strongly expanding ($\theta_{0.75}$) and declining ($\theta_{0.25}$) firms can be analysed in addition to the median growing firm ($\theta_{0.5}$). Our intuition is that high growth events, a dominant feature of firm growth, rely differently on internal as well as external factors. Technical details are described in KOENKER (2005). Here we only point out that, likewise to OLS regression, the coefficient estimates can be interpreted as partial derivatives, meaning the impact of a one-unit change of an independent variable on the firms' growth rate at the θth quantile holding all other variables fixed.

4.3 Identification of decay function parameters

Social interactions are fundamental to all mechanisms that underlie agglomeration economies, like labour market pooling, contracting with suppliers and customers, transfer of knowledge, but even local competition. From simple transaction cost reasoning, the frequency of interactions should decay with distance. Moreover, the literature on commuting behaviour (JOHANSSON et al. 2003, ANDERSSON and KARLSSON 2007) shows that the negative travel time sensitivity is not linear in space, but varies between different geographical scales: within a narrow local context, interactions can take place at short notice and are primarily governed by randomness (THORSEN et al. 1999). Thus, within agglomerations interactions are only marginally affected by distance. At some threshold distance, however, the minimal cost principle predominates and consequently, the frequency and contribution of growth relevant economic interactions become highly distance-sensitive and may decrease rapidly. This threshold can be said to define the range of the region from a firms' perspective. For very long distances, geography ceases to matter once again. Mathematically, these behavioural assumptions can be expressed as a S-shaped and downward sloping log-logistic decay function of travel time *d*:

$$f_{r,s}(d) = 1/(1 + r^{-s} * \exp(s * \log(d))) = 1/(1 + (d/r)^{-s}) \tag{4}$$

with *r* and *s* representing two parameters that describe the shape of the curve (see DEVRIES et al. 2009 for technical details). Parameter *r* determines the location of the curve's inflection point, and parameter *s* its degree of steepness. The curve starts rather flat with the value of 1, becomes steeper, and then gradually flattens again to approach 0. If *s* becomes 1, the curve takes the shape of a negative exponential function. If *s* tends towards infinity, the function resembles a binary distance circle, with values of 1 for distances below *r*, and 0 for distances above *r*. Keeping *r* constantly at 90 minutes, figure 1 depicts five curves for different values of *s*.

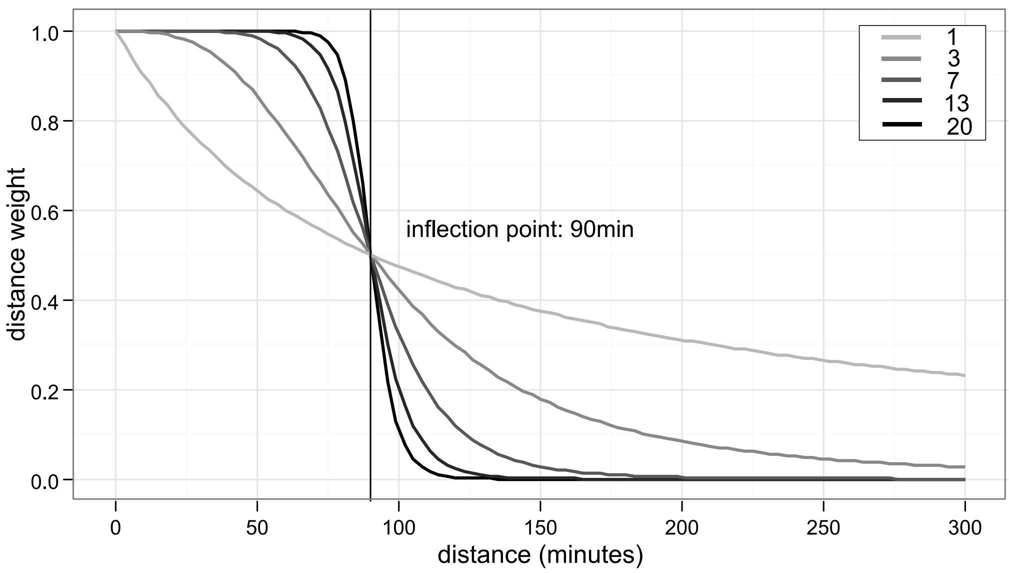

Figure 1: Log-logistic decay function for inflection point *r* = 90min and different degrees of steepness *s*

To identify the best specification of $f_{r,s}(d)$, the two variables *AGGL* and *KNOW* are regressed on the growth rates for each industry, for each quantile θ, as well as for each possible integer combination of the parameters r and s within the intervals [5, 300] and [1, 20], respectively. The smallest log-likelihood value gives the best fitting combination of r and s. Furthermore, the confidence intervals around these parameters, which contain plausible alternative specifications of $f_{r,s}(d)$, are determined using the likelihood ratio test. As illustrated in figure 2 for two exemplary cases, besides a straightforward single optimum scenario like in textiles for the variable *AGGL* at $\theta_{0.5}$, also multiple optima are feasible: firm growth in financial services are related to scientific publications at a narrow local scale, expressed by a decay function with r = 11 minutes and a sharply declining shape of s = 20, and simultaneously at a wider spatial range with r = 300 and s = 1. In cases such as the latter, all significantly distinguishable optima will be included into the regression model as separate decay function specifications. However, never more than two optima are identified in any single case.

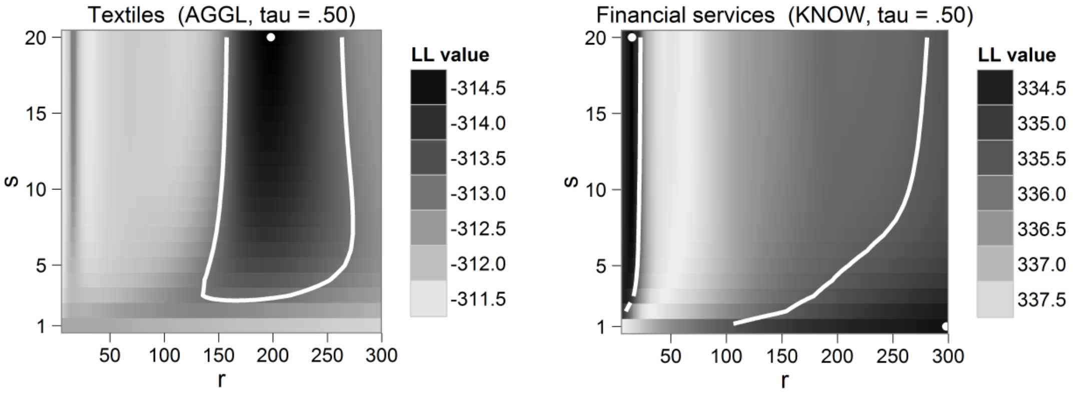

Figure 2a and *2b*: Examples of decay parameters optimization procedure with one minimum (left) and two minima scenario (right). Minima are shown as white points, confidence interval borders are shown as white curves.

5 Results

5.1 Distance decay function specification

Figure 3 provides an overview on the estimated parameters of the distance decay function for each industry. The optimization procedure tends to converge to two decay function specifications: on the one hand, to a slowly decaying exponential function with an inflection point at large distances; on the other hand, to an abrupt decay at very short distances. The former case concerns industries like automotive or production technology, in which the spatial impact of own-industry employment and publications on firm growth does not abruptly cease at traditionally defined regional boundaries. In other cases, the exponential decay function, often used in the literature, is significantly outperformed by specifications rather similar to distance bands. For instance, in processed food regarding *AGGL*, or in heavy machinery regarding *PUBL*, clear boundaries of agglomeration effects stand out. Both opposing specifications are simultaneously visible in the examples of distribution (for *AGGL*) or financial services (for *PUBL*), meaning that different spatial scales may matter at the same time. Finally, in industries like telecom (for *AGGL*) or transportation & logistics (for *PUBL*) the confidence intervals suggest that all specifications are feasible. To conclude, this apparent industry-specific heterogeneity highlights the importance of a sound and flexible distance decay function specification to assess the impact of industrial clusters, which otherwise would be biased by the MAUP.

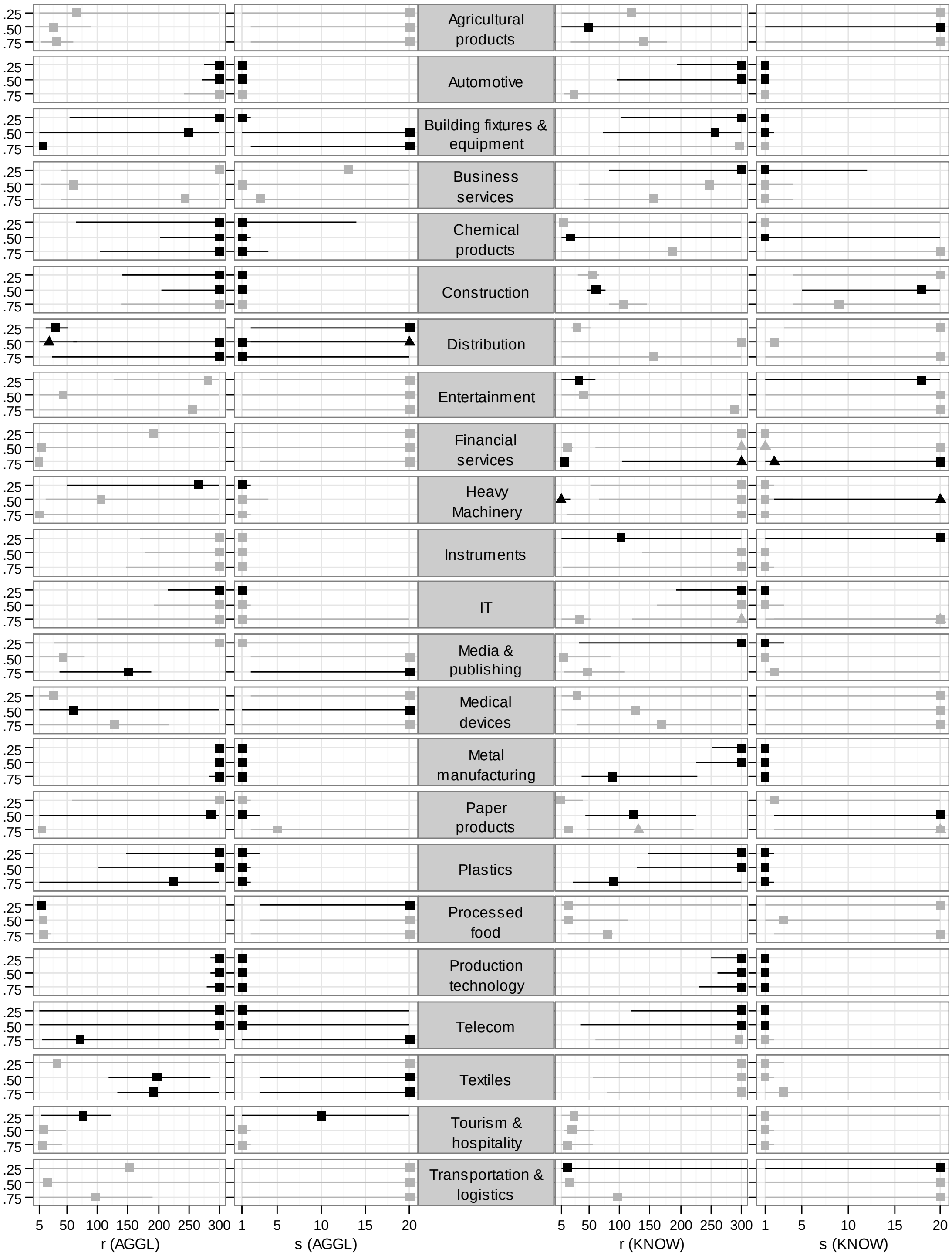

Figure 3: Estimated distance decay function parameters *r* (inflection point) and *s* (degree of steepness) with confidence intervals. Significant results (at 5%) are coloured black, a possible second optimum indicated by a triangle symbol.

5.2 Control variables

The estimated coefficients of the control variables are in line with the current literature on firm growth and industrial dynamics. For the sake of brevity, the main findings are only summarized.[3]

First, yearly growth rates always negatively correlate with the firms' size and in most industries also with age. This confirms the literature (e.g., EVANS 1987) rejecting GIBRAT's law which assumes that growth is independent of size (and age). The revealed relationships become even more pronounced for highly growing firms at the conditional quantile $\theta_{0.75}$. Only for shrinking firms, at $\theta_{0.25}$, the growth relationship vanishes for age and becomes even positively significant for size in most industries. These patterns simply imply that the growth of larger and older firms is less volatile: they are less likely to realize large growth jumps, and at the same time they are less prone to strong negative growth events. Since HYMER and PASHIGIAN (1962), this negative relationship between growth rate variance and firm size is well studied.

Second, in one third of the analysed industries, population density, a general measure of urbanization economies, comes along with lower average growth rates. The only exception is found in entertainment, where being located in high density districts means higher growth prospects. At the lower and higher quantile, its influence diminishes and remains significant in a handful of industries only. This finding confirms other studies of Germany (e.g., FORNAHL and OTTO 2008) and suggests that cost aspects due to congestion in densely populated places dominate when agglomeration effects of own-industry employment and proximate publications are directly taken into account. Similar findings can be reported for the unemployment rate, measuring the general structural and economic conditions, for which the correlation also tends to be negative in most industries, with the exceptions of construction and plastics.

Third, the two border-region dummies, which control for a potential underestimation of agglomeration economies across national boundaries, are merely significant. However, growth rates are, not surprisingly, significantly reduced during the years of the financial crisis. Only firms operating in agricultural products and paper products have shown to be resistant to the macroeconomic recession. Finally, being a subsidiary firm primarily matters for shrinking firms: with the support of a parent company, strong negative growth impulses seem to be cushioned more easily.

5.3 Impact of own-industry employment and publications

Having controlled for various firm and region-specific variables, the impact of the spatially discounted location variables can be discussed. Before taking a closer look at certain peculiarities at the industry-level, emerging general patterns are highlighted.

Being located in proximity to employees of the same industry (*AGGL*) reduces the firms' growth prospect (see table 3). For the median growing firm, this relationship is significantly negative in ten out of 23 analysed industries, whereas it is significantly positive only in medical devices and distribution. In the latter industry, even two relevant spatial scales matter at the same time. At the lower quantile $\theta_{0.25}$, 12 significantly negative cases versus one positive case are found, and at $\theta_{0.75}$ the ratio is seven negative versus two positive relationships. This tendency is reflected by a steady increase of the average size of the coefficients from -0.0005 at $\theta_{0.25}$, to -0.0003 at $\theta_{0.5}$, and to -0.0001 at $\theta_{0.75}$, which still remains below zero. Table 4 reveals a general positive relationship between firm growth and nearby scientific publications (*KNOW*). For the median growing firm, the relationship is significantly positive in eight of the analysed industries compared to two negative cases. At $\theta_{0.25}$, 11 positive cases stand against two negative ones, and at $\theta_{0.75}$, the ratio is four versus one. Also for *KNOW*, starting from a positive sign, the coefficients, on average, tend towards zero for higher quantiles: 0.0036 at $\theta_{0.25}$, 0.0018 at $\theta_{0.5}$, and 0.0005 at $\theta_{0.75}$.

These general patterns allow two conclusions. First, agglomerations of own-industry employment do not stimulate or even hamper the growth of firms. This finding is in line with the literature that acknowledges cluster effects on start-ups (e.g., SORENSEN and AUDIA 2000), yet negating the positive effects on growth of already established firms (FRENKEN et al. 2011). For some industries the lower growth prospects of firms located in more agglomerated areas suggest that the spatial concentration process of industrial activities is reversed.

On contrary hereto, nearby scientific publications tend to increase the firms' growth prospects, hence underlining the vast amount of literature on knowledge spillovers in general, and on the impact of R&D and universities in particular. Bridging the two measures for economic and knowledge generating activities by conjointly plotting the estimated coefficients (see figure 4), a negative relationship emerges. This supports the idea that industrial clustering is not an infinite self-reinforcing process, as the two external factors on firm growth show counter-balancing tendencies. Second, there is clear tendency that both the general positive impact of *KNOW* and the negative impact of *AGGL* vanishes for better performing firms. Strong positive growth events are less dependent on economic and knowledge generating activities in the firm's proximate surrounding. But for highly shrinking firms, the location is even more relevant: negative growth events become more likely in areas with a strong agglomeration of own-industry employment, possibly due to higher competition effects or to a higher dependency on the development of surrounding firms that increases vulnerability to industry-specific problems. Nearby scientific publications, however, make negative growth events less likely to occur, indicating that new knowledge might protect firms from declining and reduces the vulnerability to shocks.

Table 3: Coefficients for *AGGL* at different quantiles

ID	Name	*AGGL* $\theta_{0.25}$	$\theta_{0.50}$	$\theta_{0.75}$
1	Agricultural products	-0.0002 ‘	0.0000	-0.0000
2	Automotive	-0.0004 **	-0.0004 ***	-0.0002
3	Building fixtures & equipment	-0.0009 *	-0.0003 **	-0.0001 **
4	Business services	-0.0001	-0.0000	-0.0000
5	Chemical products	-0.0003 *	-0.0005 ***	-0.0004 ***
6	Construction	-0.0006 *	-0.0004 **	-0.0000
7	Distribution	0.0001 *	0.0012 * 0.0001 *	0.0036 **
8	Entertainment	0.0005	-0.0001	0.0005
9	Financial services	0.0000	-0.0000	-0.0000
10	Heavy Machinery	-0.0014 **	-0.0003	-0.0002 ‘
11	Instruments	-0.0003	0.0007	0.0009
12	IT	-0.0007 *	-0.0007 ‘	-0.0003
13	Media & publishing	0.0000	-0.0000	0.0003 *
14	Medical devices	-0.0000	0.0001 *	-0.0002
15	Metal manufacturing	-0.0020 ***	-0.0016 ***	-0.0016 ***
16	Paper products	-0.0002	-0.0009 ***	-0.0000
17	Plastics	-0.0018 ***	-0.0016 ***	-0.0018 ***
18	Processed food	-0.0001 *	0.0000	-0.0000
19	Production technology	-0.0011 ***	-0.0012 ***	-0.0009 *
20	Telecom	-0.0009 *	-0.0008 **	-0.0001 *
21	Textiles	0.0000	-0.0004 ***	-0.0006 ***
22	Tourism & hospitality	-0.0003 *	-0.0003	-0.0003
23	Transportation & logistics	-0.0000 ‘	-0.0001 ‘	0.0001 ‘
Significantly *positive* cases (at 5%)		1	3	2
Significantly *negative* cases (at 5%)		12	10	7

*p-values: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*

Table 4: Coefficients for *KNOW* at different quantiles

ID	Name	***KNOW*** $\theta_{0.25}$	$\theta_{0.50}$	$\theta_{0.75}$
1	Agricultural products	0.0003	-0.0002 *	-0.0006
2	Automotive	0.0049 ***	0.0024 **	0.0002
3	Building fixtures & equipment	0.0037 *	0.0025 *	-0.0010
4	Business services	0.0103 *	0.0032	-0.0007
5	Chemical products	0.0005	0.0010 **	-0.0001
6	Construction	-0.0001	-0.0006 **	-0.0002
7	Distribution	0.0002	-0.0008	-0.0015
8	Entertainment	-0.0008 **	-0.0002	-0.0016
9	Financial services	0.0002 -0.0002	0.0002 ‘	0.0006 ** -0.0034 *
10	Heavy Machinery	0.0023 ‘ 0.0001 *	0.0013	0.0015 ‘
11	Instruments	0.0006 **	0.0004	0.0000
12	IT	0.0052 ***	0.0021	0.0005 ‘ -0.0003
13	Media & publishing	0.0043 **	-0.0001	-0.0012 ‘
14	Medical devices	-0.0000	-0.0004	0.0003
15	Metal manufacturing	0.0248 ***	0.0182 ***	0.0101 ***
16	Paper products	-0.0002	0.0004 **	0.0001 0.0004
17	Plastics	0.0068 ***	0.0039 **	0.0033 *
18	Processed food	-0.0000	0.0001	-0.0003
19	Production technology	0.0133 ***	0.0105 ***	0.0062 *
20	Telecom	0.0035 ***	0.0017 *	0.0019 ‘
21	Textiles	0.0011	-0.0002	-0.0007
22	Tourism & hospitality	0.0010	-0.0010	-0.0001
23	Transportation & logistics	-0.0003 **	-0.0000	-0.0004
Significantly *positive* cases (at 5%)		11	8	4
Significantly *negative* cases (at 5%)		2	2	1

*p-values: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*

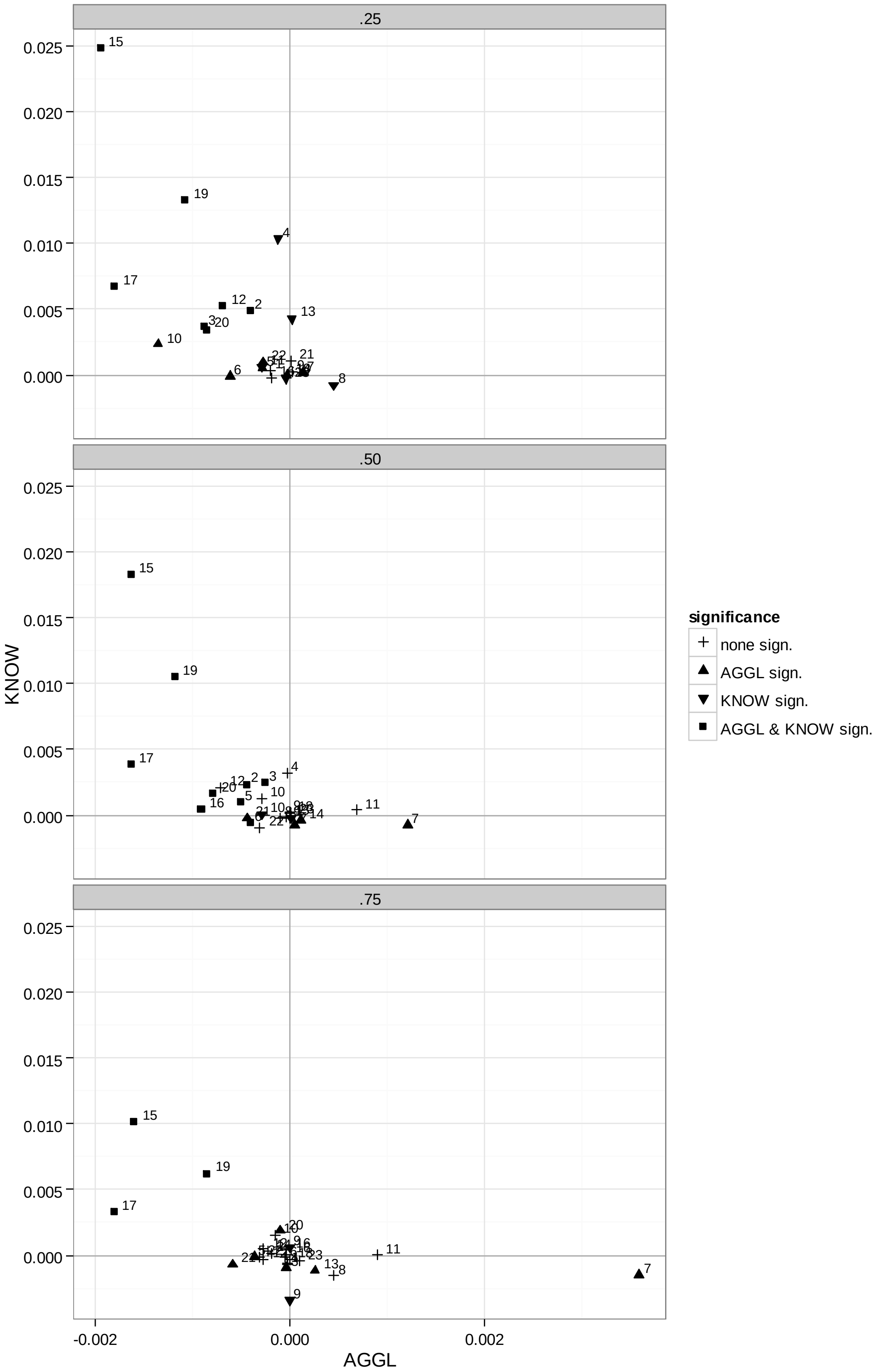

Figure 4: Scatterplot of coefficients β_1 (*AGGL*) and β_2 (*KNOW*) for different quantiles. Significant results (at 5%) are indicated by the symbols.

In section 2, it is hypothesized that the actual impact of *AGGL* and *KNOW* on firm growth should depend on the current stage of the clusters' lifecycle, which can be roughly approximated by the average age of the industries' firms. Correlating this age with the corresponding regression coefficients reveals that negative agglomeration economies are more pronounced in older industries (see table 5). In particular, firms of these industries are significantly more likely to decline strongly. In mature stages also the generation of new knowledge takes on greater relevance, especially for the ability of realising larger growth jumps. Considering the results from above, it also means that for younger industries both the agglomeration of own-industry employment and the presence of nearby publications play a smaller role.

Table 5: Pearson's correlation coefficients of β_1 (*AGGL*) and β_2 (*KNOW*) with the industries' age.

	$\theta_{0.25}$	$\theta_{0.50}$	$\theta_{0.75}$
β_1 (*AGGL*)	-0.364 (0.046)	-0.241 (0.247)	-0.134 (0.523)
β_2 (*KNOW*)	0.137 (0.512)	0.257 (0.205)	0.366 (0.060)

p-values in parentheses

Although some general patterns are identified, a high heterogeneity apparently exists at the industry-level: firms of the various industries are not affected by the economic and scientific landscape in the same way. For illustrative reasons, three industries are analysed more in-depth: chemical products, distribution, and tourism & hospitality.

Chemical products are composed of primarily science-based industries according to PAVITT (1984). Not surprisingly, being located in proximity to scientific publications increases firms' general growth prospects. Although the positive relationship is identified for the entire analysed spatial range up to 300 minutes, it is most distinctive at 20 minutes, showing the importance of face-to-face contacts despite the high codifiability of the rather analytical knowledge base (ASHEIM and GERTLER 2005). High positive and negative growth events are not affected by nearby publications, probably due to the importance of other reasons like fluctuations in global market conditions. *AGGL* shows for all quantiles a negative impact at a larger spatial scale. As firms in these industries are relatively old (median age of 24), most clusters have already arrived at later stages of their lifecycle, in which negative agglomeration economies predominate. Although partly less knowledge intensive, similar results are observed for automotive, building fixtures & equipment, heavy machinery, IT, metal manufacturing, paper products, plastics, and telecom.

In accordance with BEAUDRY and SWANN (2009), service firms tend to be less influenced by their surroundings than manufacturing firms. For instance, *KNOW* is not relevant for firms in tourism & hospitality, and AGGL only negatively relates with firm growth at $\theta_{0.25}$: fierce competition within the travel time distance of one or two hours seems to make some firms strongly losing ground. Likewise unaffected remain business services and entertainment firms. Only in media & publishing, firms are more likely to thrive when located in clusters with related firms.

Finally, firms belonging to distribution industries compose a rather special case. As expected, *KNOW* does not matter, but all the more so does *AGGL* in a positive way. Here, the spatial scale is particularly interesting: a high concentration of own-industry employment within a 30 minutes radius (because the decay function sharply declines) significantly reduces the likelihood of high negative growth events. Highly positive growth events, by contrast, are visible at a larger spatial scale. For the average firm, both spatial dimensions become significant, underlining the old wisdom that optimal location choices always require complex spatial multi-level decisions, above all in the distribution industries.

6 Conclusions

FRENKEN et al. (2011) have suggested for future research that one of the main challenges "lies in settling contradictory empirical findings. In particular […] the main gap in our empirical understanding concerns the effect of localization economies on firm performance, which some may even consider the key question in economic geography at large". In line with these authors, this paper argues that contradictory empirical findings are closely related to the heterogeneity of firms and industry they belong to, and of the spatial economic landscape they are located in.

This paper takes the call for a finer resolution seriously. Several methodological choices are made to account for the omnipresent heterogeneity. First, the approach is micro-geographic in nature, as both, the firms and sources of agglomeration economies are geolocated in space. The unevenly distributed infrastructure which determines the accessibility to these growth relevant external sources is modelled via travel times in the road network, and behavioural assumptions of spatial interactions are reflected by the log-logistic distance decay function. Moreover, distance-based methods make choices regarding the definition (of the existence) and spatial boundaries of industrial clusters obsolete. Second, related economic activities are distinguished from knowledge generating activities by measuring own-industry employment as well as scientific publications in each municipality. Here, the identification of the best fitting decay function specification is performed for both variables separately, as the "relevant spatial level and spatial decay may well be different for different mechanisms underlying localization externalities" (FRENKEN et al. 2011: 21). Results show that the spatial impact of agglomerations effects are in some cases a sub-regional phenomena, whilst in other cases transcending traditionally defined regional boundaries. Third, quantile regression techniques shed light on differences in the relationship between highly growing and declining firms and agglomeration economies. As theorized by HOOGSTRA and VANDIJK (2004), better performing firms tend to be less constrained by their spatial surrounding, which, however, is more influential for highly declining firms. Finally, the disaggregated level of industries accounts for heterogeneity in the underlining technologies and differences along the lifecycle stages. Both aspects have increasingly gained attention in the recent literature. Our results confirm the existence of differences and particularities when comparing agglomeration economies systematically across industries and support the idea that the relevance of agglomeration economies depends on the industry's age and hence on its stage in the lifecycle.

Despite the high flexibility of the modelling assumptions, a rather coherent picture of the effects of industrial clusters on firm growth emerges. Being located in agglomerations of related economic activities does not increase the firms' growth prospects. In many industries, even negative agglomeration economies significantly prevail. Especially events of strong decline become more likely to occur in such environments, foremost in industries which have arrived at later stages of their lifecycle.

This finding seems to contradict the usual belief that firms benefit from being located in a cluster. PORTER and his co-authors find in several papers that within clusters wages, innovativeness and entrepreneurship are higher (PORTER 2003 and DELGADO et al. 2012). In contrast, other researchers do not find higher survival rates for firms located in clusters (BUENSTORF and KLEPPER 2009). Besides higher start-up rates in clusters, which are confirmed in all studies of this kind, the other seemly contradictory findings may be explained as follows: Firms in clusters benefit from the surrounding in terms of higher innovativeness and competitiveness, but they have to pay higher wages for their employees. As a consequence, they do not show higher profits and growth rates. Simpler business activities might even be moved outside of cluster places, where wages are lower, so that the number of employees might even shrink as found above. If we consider the cluster lifecycle, such a view is further confirmed: In the early phase of the cluster lifecycle firms in clusters show higher growth rates, but in later phases we do not find such higher average growth rates because this would imply that clusters continue to grow without a limit - something that we do not observe in reality. Interestingly, this interpretation of the findings implies that firms in mature clusters do not make higher profits, but also implies that wages and, thus, value added and taxes are higher in mature clusters. Hence, it is the region and the people therein that benefit from mature clusters, which makes clusters a relevant policy issue.

Proximate knowledge generating activities, which more directly reflect the specific mechanism of knowledge spillovers, tend to be positively related to firm growth. New scientific knowledge seems to play an important role in counterbalancing negative agglomeration effects from competition of related firms. Exceptions of these general patterns exist, and often can be explained by taking a closer look at properties and particularities of the respective industries.

Endnotes

[1] A quadratic term to control for nonlinear relationships was initially included, but never found to be significant.

[2] Performing an extensive Monte Carlo analysis, these authors show that this approach captures substantive spatial dependence in the dependent variable and accounts for both local and global spillovers.

[3] The detailed regression results of the control variables are available on request.

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