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The effect of clusters on the survival and performance of new firms

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Abstract This paper contributes to the literatures on entrepreneurship and economic geography by investigating the effects of clusters on the survival and performance of new entrepreneurial firms where clusters are defined as regional agglomerations of related industries. We analyze firm-level data for all 4,397 Swedish firms started in the telecom and consumer electronics, financial services, information technology, medical equipment, and pharmaceuticals and pharmaceutical sectors from 1993 to 2002. We find that that firms located in strong clusters create more jobs, higher tax payments, and higher wages to employees. These effects are consistent for absolute agglomeration measures (firm or employee counts), but weaker for relative agglomeration measures (location quotients). The strengths of the effects are found to vary depending on which geographical aggregation level is chosen for the agglomeration measure.

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1 Introduction

Clusters, which are defined as geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries and associated institutions (Porter 1998, p. 197), have attracted much attention in the academic literature. Numerous studies have examined the effect of clusters either on the level of individual firms or on the aggregate level of regions or nations. Clusters have also become a tool or framework for economic policy (European Commission 2003). Since the 1990s, a large number of cluster organizations have been formed as public–private partnerships with the purpose of promoting the growth and competitiveness of clusters (Ketels et al. 2006; Sölvell et al. 2003).

Entrepreneurship is commonly held to be enhanced in regions with strong clusters. New entrepreneurial firms are attracted to clusters by the pool of skilled and specially trained personnel, access to risk capital, favorable demand conditions, reduced transaction costs, and motivational factors, such as prestige and priorities (Krugman 1991; Marshall 1920; Storper 1997). Conversely, entrepreneurship

strengthens clusters through the increased rivalry that new entrants bring (Krugman 1991; Porter 2003). Despite the considerable body of existing empirical cluster research, few studies have systematically investigated the effect of clusters on the performance of new entrepreneurial firms, and existing research shows inconsistent results concerning whether new firms are positively affected, not affected, or even negatively affected by locating in a cluster (Rocha 2004). While a number of studies have found that clusters enhance the probability of entry, survival, and growth of new firms (Beaudry and Swann 2001; Dumais et al. 2002; Pe'er and Vertinsky 2006; Rosenthal and Strange 2005; Stough et al. 1998), other studies indicate that location in a cluster decreases the survival chances of new firms (Folta et al. 2006; Sorenson and Audia 2000).

An economic explanation for such a potentially negative effect is that while moderate levels of clustering are beneficial for new firms, very strong clusters might produce adverse effects due to congestion and hyper-competition among firms for resources and personnel (Beaudry and Swann 2001; Folta et al. 2006; Prevezer 1997). An alternative sociological explanation suggests that specific socio-cognitive effects account for the presence of clusters, independent of economic advantages. In this perspective, clusters arise from easier access to resources for launching a new firm and from exaggerated expectations of success due to skewed perceptions of entrepreneurial opportunities, leading to an increase in start-up rates (Sorenson and Audia 2000; Sørensen and Sorenson 2003). This explanation challenges the assumption that the existence of clusters implies the existence of some underlying economic benefit.

The effect of clusters on entrepreneurship is therefore an area where further empirical research is needed (Rocha 2004). In this paper, we examine the effect of clusters on the economic performance of new firms. Specifically, we investigate how the relative strength of the cluster in which a new firm is located influences the firm's probability of survival and its ability to create jobs and pay taxes and salaries. In an attempt to bridge the conflicting evidence of earlier studies, we approach the problem in a manner that is distinct from previous studies in three ways. First, we attempt to bridge the empirical gap between firm-level cluster effects and region-level outcomes. Second, we apply the cluster framework by operationalizing clusters as aggregate groups of related industries. Third, we rely on a large and unbiased dataset that tracks the full population of Swedish firms started in one of five different cluster categories over a period of 10 years.

The attempt to establish a micro-level link between firm-level cluster effects and region level outcomes represents the first contribution of this paper. It is believed that the economic benefits of clusters represent mechanisms that enhance the productivity of the individual firms through the proximity to other firms (e.g., Marshall 1920; Saxenian 1985; Storper 1997). These economic benefits, such as labor pooling, the presence of specialized suppliers, and knowledge spillovers, do not benefit the regional economy directly, but rather indirectly by allowing firms to expand more rapidly, pay higher salaries, and have higher rates of innovation (Audretsch and Feldman 1996; Porter 2003). *Regional-level* studies that identify a relationship between greater cluster strength and regional economic performance (e.g., Braunerhjelm and Borgman 2004; de Blasio and Di Addario 2005, Porter 2003) imply—but do not show—that the benefits found on the regional level have come about as the aggregated result of the corresponding benefits for the individual firm. *Firm-level* studies of cluster are usually concerned with performance indicators relevant for the firm itself, such as profitability or the ability to attract external capital (Folta et al. 2006). Such studies provide evidence of economic benefits from clusters for the individual firm, but do not demonstrate that cluster effects actually translate to economic benefits for the region. Our study thus responds to a call for studies investigating "the way in which fortunes of firms and regional clusters intertwine" (Feldman 2003, p. 311) by conducting a firm-level analysis of not only survival, but also of economic output variables that are directly relevant for the regional economy: job creation, salary payment levels, and tax payment levels.

The second contribution of this paper is an operationalization of clusters as aggregate groups of *related industries*. When studying industrial agglomeration one can aggregate industries in different ways, from narrowly defined industries to widely defined sectors, such as "manufacturing industry." Yet, there is evidence that upstream–downstream linkages produce co-localization patterns between certain industries (Dumais et al. 2002) and furthermore that

technological linkages between related industries are an important factor for innovation in those industries (Scherer 1982; Feldman and Audretsch 1999). The presence of such external economies from linkages in shared factor inputs, technologies, knowledge, skills, and institutions, suggest that neither the individual industry nor the wide industry sector (operationalized as a higher level of some industry classification system) is the best unit for studying cluster effects. Following Porter (2003), we therefore define aggregate groups of related industries forming cluster categories that are wider than the industry level, but narrower than the broad sector level.

The third contribution of this paper is that it is based on a complete and unbiased population sample of all firms started within an industry in one of five different cluster categories. While many prior studies have relied on regional populations of firms or samples of firms drawn across a whole nation, our analysis is based on a full population consisting of every Swedish firm started within an industry in one of five different cluster categories over a period of 10 years, in total 4,397 firms. We are thus confident that our findings are not driven by the specific sampling procedure.

In this study, we find evidence that location in strong clusters is highly related to economic benefits for new entrepreneurial firms. Cluster strength is found to have a strong and significant effect on firm survival, job creation, VAT payments, and salary payments. These effects vary depending on for which geographical level the data are aggregated, indicating one possible reason for the conflicting evidence in earlier studies. For salary payments, the results are stronger if cluster effects are measured on the largest geographical level, whereas for firm survival the results are most prominent if cluster effects are measured on the smallest geographical level. We also find that absolute agglomeration values (counts) have overall stronger impact than relative agglomeration values (location quotients).

This study provides theoretical and empirical contributions to the discussion of agglomeration in entrepreneurship and economic geography research. To the best our knowledge, it is the first study to actually measure the firm-level the micro-economic impact of clusters on new firms in terms of job creation, wage levels, and tax payments. The study also has policy implications in that it lends support to entrepreneurship policy programs based on clusters.

2 Economic benefits of clusters

Industrial agglomerations have been a topic of economic theory for more than a century. Over time, a number of theories have been formulated that suggest effects that could explain the existence of industrial agglomerations. In general, two fundamental types of external economies have been proposed. *Urbanization economies* convey the benefits of the concentration of economic activity, regardless of its type, in a specific city or a region, while *localization economies* convey the benefits of a specific industry or a group of related industries that are localized in a region. (For overviews, see Malmberg et al. 1996; Rosenthal and Strange 2004.) In this study we will focus on localization economies, while including urbanization effects as a control variable.

In broad terms, localization effects can be categorized as related to three theoretical areas: transportation costs, external economies, and socio-cognitive effects. Transportation costs and external economies represent economic benefits for the firm that can potentially translate to economic benefits for the region; socio-cognitive effects do not. The first line of theory suggests that industries locate close to resources in order to minimize transportation costs. This theoretical approach traces its roots to von Thünen (1826), who explained the distribution of different types of agricultural production around a town center with transportation costs to the buyer. Later, Weber (1909) attributed the location patterns of industrial production units to the transportation costs from suppliers.

Contemporary focus has shifted towards the second theoretical approach, which suggests that firms benefit from industrial agglomerations through efficiency gains related to *specialization*. Marshall (1920) points to three mechanisms: industry specialization, labor pooling, and knowledge spillovers.

With the presence of many similar firms, firms can pursue a higher degree of intra-industry specialization and thus achieve higher productivity. In addition to these gains from intra-industry specialization, economic benefits can also be gained from inter-industry specialization where specialized suppliers and subsidiary industries provide inputs that enhance the performance of the core industry. *Transaction-cost* effects can be seen as a variation of Marshall's specialization argument (Rocha 2004; Storper 1997), where proximity of buyers and sellers in an industrial agglomeration makes it easier to

make deals and deliver products to each other, reducing the costs associated with vertical disintegration. Similarly, lower *search costs* make it easier for entrepreneurs to find buyers and to be found themselves (Stuart 1979). Regions with higher agglomeration also offer greater communication advantages as firms develop better knowledge of each other (Saxenian 1985).

Marshall also stresses the local labor market as a source of economic benefits. Specialization allows firms to benefit from access to a *pool of specialized labor,* which also enhances economic performance.

Marshall's third main mechanism has to do with the flow of knowledge between firms. *Knowledge spillover* occurs when knowledge flows between firms through social interaction or, to use Marshall's famous quote, "[t]he mysteries of the trade are […] in the air" (Audretsch and Feldman 1996; Marshall 1920, pp. IV.X.7). The argument is based on the flow of information between individuals working in the same region. Knowledge is more likely to spill over between firms and workers in geographic proximity, and geographic proximity facilitates the formation and transmission of social capital, thus enhancing trust and the ability to share vital information. Further, increased *rivalry* implies that neighboring agglomerated firms stimulate each other to reach a higher level of innovation and performance. Local competitors create a higher degree of rivalry and may lead to a local struggle for "bragging rights" (Porter 1990).

A final theoretical approach explains the existence of industrial agglomerations from the perspective of organizational sociology. Here, *sociological and cognitive effects* are resources needed to start a firm if it is located far away from those resources. This increases the entry rate in clusters, but is not necessarily coupled with enhanced performance for those newly started firms. Locally increased ease of entry and exaggerated expectations of success would therefore account for cluster formation (Sørensen and Sorenson 2003). In a study of the US shoe industry, Sorenson and Audia (2000) found that both entry rates and failure rates were higher among concentrated plants, leading them to conclude "that variation in the structure of entrepreneurial opportunities, rather than variations in the economics of production and distribution, maintains geographic concentration in the shoe industry" (Sorenson and Audia 2000, p. 427).

Many of these theoretically proposed benefits of clusters have been studied empirically. Some of these studies have investigated these economic benefits of cluster on the firm level. For instance, Baptista and Swann (1999) investigated 674 American and 1,339 British firms in the computer industries and found that new entrepreneurial firms were more likely to be started in clustered regions. Beaudry and Swann (2001) studied 137,816 UK firms in 57 two-digit SIC industries and found that firms grew faster in clusters, and also that new firms were attracted to clusters, especially in the finance, computer, motor, aerospace, and communications manufacturing industries. Beaudry and Breschi (2003) examined the impact of agglomeration on patenting among firms in 65 UK counties and 95 Italian provinces. Their findings indicated that high cluster employment in a firm's own industry in itself did not contribute to patenting, but that there was a significant effect if one measured only employment in co-located firms that were themselves innovative and produced patents. Globerman et al. (2005) studied the sales growth and survival of 204 Canadian IT firms, but found only limited location effects on sales growth for the Canadian province or metropolitan levels, and no location effects on two-digit postal code level. For firm survival, location effects were found to be even weaker. However, results were inconclusive due to the limited number of firms studied.

Other studies have investigated economic benefits of cluster on the regional level. Porter (2003) studied wages and patenting in all industry sectors across 172 economic areas covering the entire United States from 1990 to 2000. He found that high regional wages and high regional patenting were related to strong clusters, measured as the share of employment in those industry groups that were over-represented in a region. Braunerhjelm and Borgman (2004) examined 143 industries in 70 regions in Sweden from 1975 to 1999 and found that geographic concentration was positively related to labor productivity growth in a region. De Blasio and Di Addario (2005) examined a sample of 230 Italian regions and divided them into two groups: industrial districts (meeting certain criteria on manufacturing employment share, small and medium firm share, and sector specialization) and non-industrial districts. They found that industrial districts increased worker mobility and the likelihood of being employed or of starting a business, while reducing the returns to education. Fritsch and Mueller (2008) studied new

firm formation between 1983 and 2002 in the 74 West German planning regions and found that new firms founded in agglomerations led to higher job creation both in the short term (direct effects) and in the long term (supply-side effects) compared to new firms founded in rural or moderately congested areas.

These studies indicate that firms in general benefit from clustering and also that agglomerated clusters are beneficial for regional economic development. But what effects do cluster have on *new* entrepreneurial firms, given that new firms are seen as an integral part of cluster development?

3 Do new firms benefit from locating in clusters?

New firms are subject to particular difficulties in that they face a general lack of resources (Audretsch 1995), are more vulnerable to external economic shocks (Delmar et al. 2006), and frequently face cost disadvantages by operating farther from the industry's minimum efficient scale (Pe'er and Vertinsky 2006). Further, their individual founders might pursue goals that are of non-economic nature (Gimeno et al. 1997). However, many of the cluster effects that generate economic benefits for incumbent firms could apply also to new firms. Economies of specialization, labor supply, and specialized skills could make it easier for new firms to overcome their initial liabilities. Local demand effects could increase likelihood of sales and decrease transaction costs, and the competitive environment of clusters could reduce entry as well as exit barriers (Rocha and Sternberg 2005). Knowledge created by research labs and in incumbent firms flows between firms and individuals through social interaction, spurring the establishment and growth of new firms as suggested by the 'knowledge spillover theory of entrepreneurship' (Audretsch and Lehmann 2005). Whether or not such economic benefits of clusters affect new firms is the topic of this paper.

There is still little research investigating the effects of clusters on the performance of new entrepreneurial firms. Existing studies show conflicting results as to whether new firms are positively affected, not affected, or even negatively affected by locating in a cluster: Pe'er and Vertinsky (2006) investigated new entrepreneurial entrants in the Canadian manufacturing sectors from 1984 to 1998 and found that clustered firms had higher survival rates than non-clustered firms. Stough et al. (1998) investigated the economic development of the greater Washington DC area in the United States over several decades and determined that the founding and growth of new firms could be linked to a high concentration of a technically skilled population with engineering and business technology degrees. Rosenthal and Strange (2005) investigated all new plants in the greater New York metropolitan area in 2001 and found that specialization, measured as employment quotients in a local area, was positively related to job creation among new firms.

These results are contradicted, however, by other studies suggesting that new firms are adversely affected by locating in a cluster. Sorenson and Audia (2000) studied 5,119 shoe manufacturing plants in the US between 1940 and 1989 and found that plants located in concentrated regions of shoe manufacturing failed at a higher rate than isolated plants. A comprehensive study by Dumais et al. (2002) of all US manufacturing plants sampled at 5-year intervals from 1972 to 1992 found that new firms in strong clusters had higher survival probabilities, but did not positively enhance job creation in a region. Folta et al. (2006) investigated 789 US biotech firms started between 1973 and 1998. They found that stronger clusters had negative effects on the survival of new firms and that stronger clusters had positive effects on firm patenting, alliance formation, and attracting private equity partners, but only up to a certain point of cluster size, from which the positive effect decreased or turned negative as clusters grew.

We suspect that one reason for the inconsistent results of these studies is the variation in methodologies applied. Previous studies have tended to apply different levels of geographical aggregation and different measures of agglomeration, but more importantly, they have applied different levels of industry aggregation. Theoretically, the main research gap in how clusters impact new entrepreneurial firms concerns how industries are aggregated when agglomeration patterns are calculated. Table 1 gives an overview of the methodologies applied in previous studies.

Table 1 shows that most studies have examined either a single aggregation of all manufacturing industries, multiple sectors aggregated through an industry classification system (2-digit or 3-digit SIC),

Table 1 Prior empirical studies of cluster effect on new entrepreneurial firm

Study	Sample	Agglomeration model			Results	
		Geographic aggregation	Industry aggregation	Measure	Survival	Performance
Baptista and Swann (1999)	674 US and 1,339 UK computer firms in 1991	39 US states, 10 UK Central Statistical Office regions	Eight groups (computer industries)	Employee count		+ (Employment growth)
Sorenson and Audia (2000)	All 5,119 US new footwear plants in the, years 1940–1989	Distance measures applied to each plant, no geographic aggregation	One group (footwear manufacturing)	(1) Local density: inverse distance between plant and all other plants (2) national density: number of plants	–	
Nicolini (2001)	84 small firms in Lombardy, Italy, years 1992–1994	21 Lombardian districts	Three groups (textile, mechanical, wood and furniture)	Number/density of firms in a district providing service to a sector		+ (Export ratio)
Dumais et al. (2002)	300,000+ old and new US manufacturing plants, years 1972–1992	50 US States + District of Columbia	134 SIC-3 level groups (manufacturing industries)	Industry concentration based on employees in 3-digit SIC industries	+	– (Employment growth)
Globerman et al. (2005)	240 new Canadian IT firms, years 1998–2001	(1) 11 provinces, (2) 10 metropolitan areas, (3) distance to the two largest clusters	1 group (IT industries)	No agglomeration measure (model compares outcome for each region)	0	+ (Sales growth)
Folta et al. (2006)	789 new US biotech firms, years 1973–1998	85 Metropolitan Statistical Areas (based on headquarter location)	1 group (biotechnology) but with controls for four subsectors	Headquarter counts	–	+/– (Non-linear effects on patents, alliances and getting equity)
Pe'er and Vertinsky (2006)	All 48,406 new Canadian manufacturing firms, years 1984–1998	Two levels: 3,908 local Canadian areas; 289 Census Divisions	109 SIC-3 level groups (manufacturing industries)	(1) # of firms operating in same 3-SIC sector in a chosen radius around the firm (2) region with LQs larger than the median	+	
Fotopoulos and Louri (2000)	209 new Greek manufacturing firms founded 1982–1984, years 1982–1992.	Two regions, inside or outside Greater Athens	Manufacturing firms	No agglomeration measure (dummy for firms inside or outside Greater Athens)	+	

or a single industry. None of the empirical studies of cluster effects on new firms has aggregated multiple groups of related industries, despite the strong theoretical claims that firms in a cluster benefit from the competition and cooperation in geographic concentrations of firms in *related* industries. In this paper we therefore investigate how new firms in several different industries are affected by their location in clusters of related industries. In order to reconcile the contradictory findings in earlier studies we examine several different performance variables and we also try to account for the potential bias introduced by firms' attrition from the sample. Finally, we validate our findings on different geographical levels.

4 Method

4.1 Data

The dataset in this study was derived from a combination of several detailed longitudinal databases maintained by Statistics Sweden. Firm-level variables were gathered from the databases CFAR and financial variables, such as revenues and assets were collected from the Swedish tax authorities. In addition, we measure the human capital of firms by counting the number of employees with various types of post-secondary education, using the comprehensive individual-level database LOUISE.

We investigate all firms that were started between 1993 and 2002 in the areas of telecom and consumer electronics, financial services, information technology (IT), medical equipment, and biopharmaceutical industries. We chose these particular industries since they represent a wide range of knowledge-intensive manufacturing and service sectors. Statistics Sweden maintains data on all firms that register for commercial activities and/or file taxes in Sweden. The sample represents the whole population of new firms in these industries; in total 4,397 firms started during the studied period.

A common problem in studies of new firm dynamics is the change in the identification code when a firm switches ownership, industry classification, or regional affiliation (Mata and Portugal 2002). This makes an on-going firm appear as a termination and later as a new firm, while in reality it is the same firm. We minimize these problems by applying multiple identifiers as the tracking criterion and combining data from the tax authorities with identity codes from Statistics Sweden.

4.2 Cluster strength variable

In this study we use Porter's (1998, p. 199) definition of a cluster as a "geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities." Because of data limitations we must exclude associated institutions, such as universities and government agencies, from our model and focus on competing and cooperating firms in related industries. We thus operationalize cluster strength by measuring the degree of agglomeration of firms in interconnected industries. This was achieved by (1) aggregating our data geographically into regions, (2) aggregating related industries into clusters, (3) finding an indicator of economic activity relevant for cluster effects, and (4) selecting a measure to turn these indicator values into agglomeration values.

(1) We measure agglomeration on a sub-national level. Although some prominent studies (Amiti 1999; Krugman 1991; Midelfart-Knarvik et al. 2000) have examined the effect of industry localization on a national level, nations are not industrially homogenous regions, and strong agglomeration patterns occur within them. Lindqvist et al. (2003) demonstrated how the five clusters examined in this study are unevenly dispersed across 87 *labor market areas* in Sweden. These areas constitute our baseline regional aggregation level, and they cover all of Sweden, not just urban areas. However, cluster effects may reach across labor market areas, and since Sweden is a small country comparable to a mid-sized US state like Ohio, we also consider two alternative higher levels of aggregation: 21 *counties* and 8 *NUTS-2 regions*, respectively.[1] Rosenthal and Strange (2004) found that different drivers of

[1] Labor market areas are statistically defined regions used primarily to investigate regional flows of goods, workers, and production. Counties are administrative regions responsible for governmental issues such as taxation and health care. In comparison to federal nations like Germany or the US, Swedish counties have limited political independence. Counties combine to form NUTS-2 regions, which are statistical units used by the European Union to allow for the comparisons of regions of similar geography and population.

agglomeration are most pronounced on different geographical levels, suggesting that the effects of agglomeration may vary by geographical level, too.

(2) Industry aggregation levels in previous research have varied from single (Sorenson and Audia 2000) or multiple industries (Pe'er and Vertinsky 2006) to broadly defined groups of industries (Nicolini 2001) or a single group for all industries (Baptista and Swann 1999). In this study we collected data for 23 individual industries coded on the 5-digit SIC level. Similar to Gilbert et al. (2008) we therefore grouped these industries into five clusters following Porter's (2003) methodology, which in turn is based on a statistical analysis of co-location patterns of industries combined with input-output data. Porter's cluster definitions have been translated to the Swedish industry classification system, SNI-92. To test the statistical consistency of our classification, we also examined the correlation of employment quotients over time between the different industries composing a cluster. The full list of industries is shown in Appendix 1. The statistical granularity in the material varies: the Financial Services cluster comprises as many as 11 different industry codes, while Medical Equipment and Biopharmaceuticals are made up of 2 industry codes each.

(3) As an indicator of economic activity in a cluster, we base our measure on employees in the selected industry (e.g., Beaudry and Swann 2001; Glaeser et al. 1992; van Oort and Stam 2006). Specifically, we use the number of employees belonging to 1 of the 23 SIC-5 equivalent industries as a measure the relative strength of this particular cluster. Using the actual number—the count—of employees in a particular industry to measure cluster necessitates that one can control for other effects that differ between regions. In this study, we control for urbanization effects by using regional control variables for population density, employment in other industries, and the presence of universities and research institute. Because own-cluster employment is highly non-linear and varies between 0 and 26,735, results would be difficult to interpret in a linear or hazard model. Akin to many earlier studies, we instead used the logarithmic value of own-cluster employment, which is more evenly distributed between 0 and 10.19. This eases interpretation of the models. Measuring clusters based on employment has great advantages in its comparability across industry sectors. However, there are also reasons to consider cluster effects on the firm or plant level rather than the employee level. While the potential for labor specialization can be approximated by measuring the number of employees, rivalry between firms in the cluster may be more closely related to the number of firms in the cluster. Thus, to validate the findings we also estimate the empirical models using the number of plants in a cluster as an alternative base for cluster strength. We measure plants instead of firms since the latter approach would bias our measure towards headquarter-rich regions, notably large metropolitan areas.

(4) Finally, we apply two different agglomeration measures. Agglomeration can be measured in absolute terms, by using the *counts* of employees and plants, respectively, in each region. Alternatively, one can apply relative measures, *location quotients*, and relate the number of employees or plants to a reference distribution (Braunerhjelm and Carlsson 1999). In the debate on absolute versus relative measures we do not take sides, but test both measures. As reference base for the quotients we use the total employment and total number of firms in all industries, respectively, including industries outside the five clusters examined. The location quotient is thus calculated as the cluster's share of total regional employees (or plants) divided by the cluster's share of total national employees (or plants).

4.3 Dependent variables

This study investigates the local economic impact of clusters on new firms. To assess economic impact we use four different dependent variables measured at the level of the individual firm:

Survival was measured as the time from registration to the discontinuance of a firm. Similarly to prior studies of agglomeration effects on firm survival, we distinguish between firms that fail and firms that merge with or become acquired by competitors (Folta et al. 2006; Globerman et al. 2005). While termination is generally a negative outcome, merger or acquisition need not represent a sign of failure. On the contrary, divesting of their equity share can be seen as the apex of success for entrepreneurs. This suggests that terminated and merged firms should not be pooled in the survival analysis. Two statistical tests, based on a discrete choice model of the multinomial logit type,

were used to examine the validity of this assumption. We used the Wald test to compare the vector of coefficients of the terminated and the merged firms relative to surviving firms. The test revealed a statistically significant difference between the coefficients ($\chi^2 = 38.20$, d.f. $= 19$, $P < 0.05$), indicating that the two alternatives should not be pooled. A Hausman test of the Independence of Irrelevant Alternatives (IIA) showed that the coefficients for surviving and terminated firms were not affected by excluding firms that exited by merger from our analysis ($\chi^2 = 20.02$, d.f. $= 19$, $P < 0.39$). We therefore eliminated 598 merging firms from the 2,722 exiting firms, leaving us with a final 2,124 terminations.

4.3.1 VAT payments

For tax payments made by firms, corporate tax was not deemed a suitable measure. Swedish tax legislation allows privately held firms to substitute corporate tax for firm founders' earnings from outside sources, and furthermore firms can defer taxes during the first 5 years of existence. Instead, we use the logged value of VAT payments. The VAT tax rate is 25% in Sweden, and it represents 71% of total tax payments from a firm.

Job creation has frequently been examined in studies measuring the impact of entrepreneurship on economic development (Delmar et al. 2006; Hart and Hanvey 1995; Reynolds et al. 1995). To estimate the impact of cluster strength on firms' abilities to create jobs, we measure the net addition of jobs in terms of newly added employees in the firm (i.e., organic growth).

4.3.2 Wages per employee

While job creation is generally seen as an attractive outcome of entrepreneurship by policy makers, job creation per se tells little of the quality of those jobs. In order to measure the human and social dimensions of economic development (Rocha 2004), we therefore also estimated models predicting the average wages (in logarithmic form) of the jobs created by clustered and non-clustered new firms.

4.4 Control variables

We used a number of relevant control variables that prior studies have indicated as important in studies of a firm's survival patterns and performance. All control variables were updated yearly, and similar to our cluster measures, lagged 1 year to avoid problems of endogeneity.

4.4.1 Age

One of the most persistent findings in studies of new firms' development is a tendency of reduced hazard of termination as firms age (Audretsch 1995; Fotopoulos and Louri 2000). We therefore include age as a control variable in all models.

4.4.2 Legal form

New firms started as incorporations generally show much higher economic resilience than firms started as partnerships or sole proprietorships (Delmar et al. 2006). In the survival analysis we control for legal form by a dummy indicator for incorporations, which is the base category. Since the performance models were estimated by fixed effects, legal form could not be used in these because it almost never changes over time.

4.4.3 Presence of local universities

The presence of university research is argued to be an important factor for the development of a cluster and the knowledge spillovers attracting new firms to clusters (Audretsch and Feldman 1996; Beaudry and Swann 2001). As a coarse control variable for knowledge spillovers generated by public research institutions, we use the number of medical research institutions, universities, technical colleges, and business schools present in the region each year.

4.4.4 Living costs

To control for the fact that wage payments do not merely depend on the individual firm's productivity, but also on regional differences in costs of living, we include a time-variant measure of mean housing prices in the region taken from Statistics Sweden's public databases.

4.4.5 Firm's human capital

Human capital has been found to be an important predictor of firm survival (e.g., Mata and Portugal 2002) and performance (Karlsson 1997). In

particular, Pe'er and Vertinsky (2006) found that human capital had a stronger survival effect for firms at lower levels of cluster strength. We used the LOUISE database to create a variable measuring the proportion of employees with a college or university degree for each firm in our dataset.

4.4.6 Firm-specific human capital

A key characteristic for several of the industries in this study is the reliance on innovation and technological development to gain a competitive edge. Since innovation and product development in new firms are facilitated by engineering skills (Stough et al. 1998), controlling for skilled engineering personnel is important to avoid our agglomeration measure being confounded by between-group differences in such skills. Similar to Karlsson (1997), we measure the proportion of employees with an engineering or science degree working in the firm, also taken from LOUISE, to control for firm-specific human capital.

Finally, we include two variables to control for urbanization effects.

4.4.7 Other-sector employment/plants

Models based on counts will suffer a bias in that for larger or more densely populated regions, higher cluster strength values will also reflect the general size of the region, confounding cluster effects with urbanization effects. We therefore include a control variable for other-sector employment, namely the total employment in the region minus the employment in the specific cluster. In alternative models using plant measures, this control variable is also based on plants.

4.4.8 Population density

Varying degrees of urban agglomeration are not the only confounding effect in our data. Our regions are fundamentally based on administrative regions, and the delimitation between these is to some degree arbitrary. High other-sector employment could both be an effect of a higher degree of urban agglomeration (larger cities) or a wider regional scope (a larger region). To control for both these effects we also add a control variable for population density, measured as the number of inhabitants per square kilometer in the region.

4.5 Statistical analyses

To investigate the effect of cluster strength on firm survival, we used event history analysis. Similarly to prior studies of firm exit where time is measured in discrete intervals, we estimated a piecewise exponential hazard model that does not require any specific parametric assumption regarding the shape of the hazard function (Blossfeld and Rohwer 1995). This model allows the hazard to vary over yearly intervals, but constrains the covariates to shift the hazard by the same proportion each year.

To investigate the effect of cluster strength on firm performance (job creation, VAT payments, wages), we used pooled time-series regression based on generalized least squares. Model estimates with no effects, random effects, and fixed effects provided qualitatively similar results on the effects on cluster strength on the various performance metrics, but the Hausman (1978) specification test indicated that random effects were inconsistent (i.e., did not have a minimal asymptotic variance) and that fixed effects were preferable. We therefore used fixed effects estimation in all three models. To check for the presence of residuals autocorrelation, we used Drukker's (2003) implementation of the Wooldridge test (Wooldridge 2002). This indicated the autocorrelation in the residuals were present in the models on job creation and VAT payments, at or above the 1% significance level. We therefore included a control for autocorrelation (AR1) in these models.[2] This did not qualitatively alter the results; however, it significantly decreased the model fit (R^2 value). The means and standard deviations of all outcome and predictor variables, together with the correlation matrix, are displayed in Table 2, and the correlations between different cluster variables are displayed in Table 3.

[2] In unreported models we also include the lagged dependent variables to account for the endogenous nature of organic growth. The presence of this variable, however, made estimates with firm fixed effects unstable, and we excluded the lagged dependent variable in the final model. We are grateful to an anonymous reviewer for pointing out this problem.

Table 2 Variables and correlation matrix

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Survival	0.722	0.414													
2	Job creation	5.199	107.240	0.040												
3	VAT payments (log)	14.382	0.949	0.059	0.111											
4	Salary payments (log)	11.976	0.504	0.118	0.027	0.202										
5	Legal form (incorporation)	0.774	0.418	0.524	0.020	0.263	0.229									
6	Population density	43.007	90.731	0.232	0.070	0.039	0.039	−0.014								
7	House price index(log)	1.371	2.138	0.197	0.062	−0.119	−0.091	0.131	0.743							
8	Region employment(log)	4.792	5.011	0.231	0.041	0.028	0.015	−0.034	0.410	0.423						
9	Local universities	0.796	1.636	0.345	0.062	0.033	0.023	−0.003	0.896	0.763	0.419					
10	Employees(log)	0.983	0.721	0.089	0.259	0.378	0.087	0.245	0.120	0.102	−0.004	0.123				
11	Human capital	0.401	0.093	0.039	0.508	0.068	0.028	0.026	0.083	0.063	0.067	0.077	0.235			
12	Special human capital	0.089	0.388	0.159	0.340	0.219	0.111	0.139	0.217	0.242	0.270	0.225	0.580	0.385		
13	Cluster employment (log)	2.144	2.363	0.349	0.048	0.037	0.017	−0.015	0.456	0.461	0.539	0.228	0.016	0.070	0.276	
14	Inverse Mills Ratio	0.129	0.446	0.241	−0.008	−0.271	−0.084	−0.629	0.300	0.446	0.412	0.297	−0.229	−0.011	−0.030	0.410

Note: All correlations above ±0.02 significant at the 5% level. Survival and legal form variables represent yearly dummies

Table 3 Correlation between different measures of agglomeration

			Quotients (cluster specialization)						Counts (cluster size)				
	Regional base		County		NUTS-2 region		Labor market region		County		NUTS-2 region		Labor market region
		Agglomeration measure	Employment	Plants	Employment	Plants	Employment	Plants	Employment	Plants	Employment	Plants	Employment
Quotients (specialization)	County	Plants	0.913										
	NUTS-2 region	Employment	0.977	0.922									
		Plants	0.912	0.994	0.931								
	Labor market region	Employment	0.674	0.633	0.660	0.634							
		Plants	0.752	0.862	0.760	0.857	0.555						
Counts (cluster size)	County	Employment	0.887	0.756	0.908	0.769	0.576	0.595					
		Plants	0.890	0.799	0.915	0.813	0.583	0.634	0.972				
	NUTS-2 region	Employment	0.899	0.789	0.924	0.802	0.589	0.628	0.993	0.966			
		Plants	0.898	0.841	0.922	0.855	0.597	0.677	0.955	0.989	0.962		
	Labor market region	Employment	0.875	0.751	0.897	0.765	0.592	0.605	0.974	0.944	0.975	0.937	
		Plants	0.877	0.783	0.901	0.796	0.597	0.634	0.947	0.969	0.948	0.965	0.972

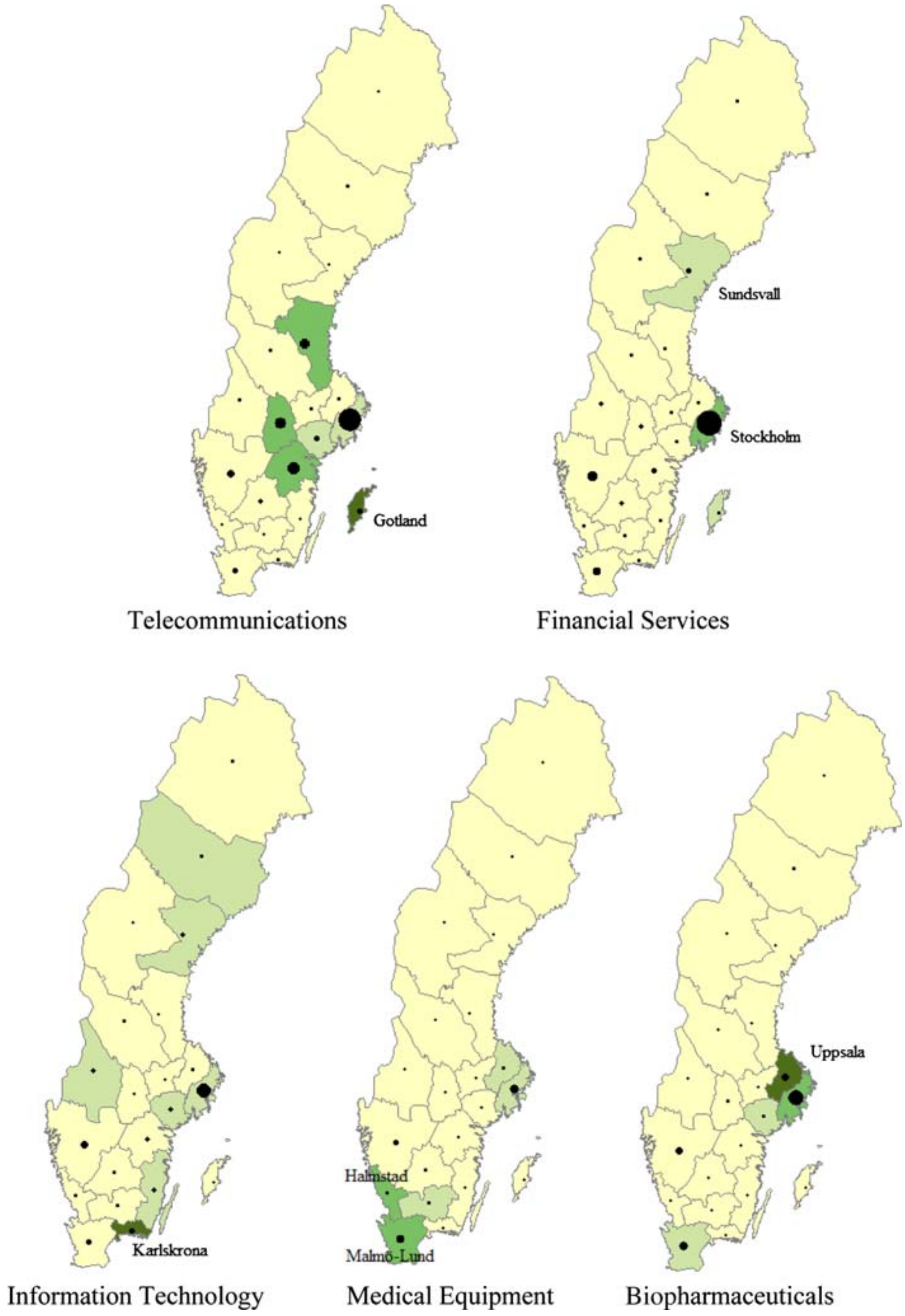

Fig. 1 Absolute and relative cluster strengths for five cluster categories in Sweden, 1997. *Notes*: Black dots indicates absolute size of a cluster (number of employees). Shaded areas represented level of specialization in the region; a darker shade is a higher degree of specialization (location quotient of plants)

5 Results

The strength of the five clusters is shown in county-level maps in Fig. 1. Absolute agglomeration (employee counts) is shown as circles where the areas of the circle represent the number of employees. Relative agglomeration (location quotients) is shown as the shades of the region; darker shades represent higher quotients. Figure 1 shows that the five clusters display quite different agglomeration patterns. As the

capital and largest city of Sweden, Stockholm is strong in all of the clusters in absolute terms, but other regions are also significant. In Telecommunications, some inland regions have high counts, and Gotland has the highest relative level of agglomeration. For Financial Services, Stockholm dominates, but the region around Sundsvall in the north is also fairly specialized due to the large number of insurance firms located there. Information Technology is spread over several regions, with the southeastern area of greater Karlskrona exhibiting the highest specialization. In Medical Equipment, Malmö-Lund has as high counts as Stockholm, but even higher relative agglomeration, as does the adjacent greater Halmstad region. For Biopharmaceuticals, Stockholm dominates together with the neighboring Uppsala region. Also the Malmö-Lund area is fairly agglomerated in Biopharmaceuticals.

All empirical models are displayed together in Table 4. The first model is the hazard model of firm survival. The exponential form of the hazard model constrains the variables to affect the hazard multiplicatively, and the coefficient estimates indicate the multiplicative effect of each variable. The

Table 4 Cluster effects on firm performance

	Model 1: survival	Model 2: job creation	Model 3: VAT payments	Model 4: salary payments
Constant	–	50.245	93.320***	10.104***
		(78.890)	(4.219)	(0.041)
Legal form = incorporation	0.170***	–	–	–
	0.011			
Population density	0.881***	−4.093	−0.125	−0.323
	(0.042)	(6.081)	(0.091)	(0.044)
House price index (log)	0.013	−6.112	0.095*	0.203**
	(2.259)	(12.066)	(0.047)	(0.030)
Other-sector employment (log)	1.032	0.000	0.002***	0.000
	(0.251)	(0.000)	(0.001)	(0.000)
Local universities	2.353	−2 .298	0.153*	0.010
	(1.353)	(7.321)	(0.054)	(0.018)
Employees (log)	0.878***	7.434	18.212***	−25.983
	(0.061)	(2.024)	(3.042)	(3.813)
Human capital	0.920**	8.241**	8.970	43.990***
	(0.120)	(2.503)	(5.020)	(4.765)
Special human capital	0.662***	33.003***	14.883*	85.442*
	(0.102)	(6.760)	(6.703)	(9.221)
Cluster employment (log)	0.902***	0.217***	0.143**	0.122***
	(0.013)	(0.035)	(0.022)	(0.016)
Inverse Mills Ratio	–	−8.690	−0.472**	−0.036
		(9.260)	(0.014)	(0.025)
Fixed firm effects	No	Yes	Yes	Yes
Log-L. value/R^2	−2449.23	0.084	0.140	0.091
Autocorrelation (AR1) control	–	0.302	No	0.321
R^2 without autocorr. control.	–	0.186	–	0.176
Firm-year obs./times at risk	12,368	10,181	10,181	10,181
Firms	3,799	3,208	3,208	3,208

Notes: Coefficients of models 1 in hazard rate format, in models 2–4 in GLS format. Standard errors in parentheses. All models include dummy variables for cohort, age, and five cluster sectors. * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$ (two-tailed)

coefficients are therefore more easily interpreted for variables that are measured in uniform units. For example, model 1 indicates that each additional employee with a college degree in science or engineering (ordinal scaled variable) decreases the hazard of disbanding by 34%, and being an incorporated firm (dummy variable) decreases the hazard of disbanding by 83%. The cluster variable in logarithmic form takes values from 0 to 10.2 and is therefore fairly easy to compare to other ordinal scaled variables. For instance, the hazard rate for a firm started in a region where own-cluster employment is 1.50 is 9% lower than in a region where own-cluster employment is 2.50. Since the standard deviation of own-cluster employment amounts to 2.36, a 1 standard deviation increase in cluster strength (i.e., being located in one of the top one-sixth clusters) increases the survival by 21%. This means that locating in an industrial cluster has a significant and meaningfully positive effect on firm survival.

We now investigate the effect of cluster strength on firm performance. Of the firms, 27% did not survive for 2 years from their formation. Since all predictor variables are lagged 1 year to avoid endogeneity, data from at least two periods are needed to assess the effect of cluster strength on subsequent performance. The firms that did not survive more than 1 year therefore had to be omitted in the performance analyses. However, if performance differs systematically between firms that survive compared to firms that do not, removing the non-survivors could induce a bias in our models. To control for this bias, we used a Heckman-type selection model to create a variable that corrects for firms' attrition from the sample. Since the error term in the first stage of the equation (the attrition model) was not normally distributed, we used Lee's (1983) generalization of the Heckman procedure by estimating a logit model of attrition from the sample, using the same variables as in the model on firm survival. The logit model used to predict the likelihood of attrition from the sample should preferably include at least one variable that influences the probability of attrition from the sample that is uncorrelated with the performance variables. For this purpose, we include the yearly regional unemployment rate that is likely to influence new firms' survival, but not their general performance since many small firms are closed down during economic booms when the opportunity costs of entrepreneurship increases, regardless of economic performance (Gimeno et al. 1997). We then included the transformed logit predictions in the form of Inverse Mills Ratios as a selection variable in the performance models (Lee 1983).

Model 2 shows the effect of cluster strength on firm job creation. Looking at the coefficient for own-cluster employment, we can see that cluster strength clearly has a positive effect on firms' abilities to create new jobs, i.e., their net number of new employees hired. Is this an important finding? If one compares the coefficients to those of the other variables, the effects do not appear to be very large. However, we cannot judge the relative magnitude of the effect in a linear model based on the coefficients alone. To do that, we need to calculate the marginal effect, i.e. the derivate of the outcome variable (job creation) divided by the derivate of the predictor variable (own-cluster employment), holding all other variables constant. Using the logarithmic value of own-cluster employment as in the hazard model on survival, this procedure reveals a marginal effect of 0.120. In other words, a firm in a region with own-cluster employment of 2.50 will have a rate of job creation 12% higher than a similar firm in a region with own-cluster employment of 1.50. A 1 standard deviation increase in cluster strength thus increases the number of jobs created by a firm by 28%. This is indeed an indication that cluster strength has a strong impact on firm job creation. Looking at the foot of Table 4, we can see that model 2 is based on fixed effects for each firm and also includes a control for autocorrelation disturbance. The same model based on random effects estimation, or alternatively on fixed effects but without the autocorrelation control, indicates qualitatively similar results. However, the explained variance is twice as high for a model without the autocorrelation control (0.19) and is more than three times as high (0.31) for a model based on random effects. The only other alterations in these alternative models are seemingly larger effects for cluster strength as well as the controls for employees and human capital without the autocorrelation control. This shows that our results are robust across different model specifications and, furthermore, indicates the existence of strong path-dependent factors that might confound the results of cluster models if one cannot properly control for such factors.

Model 3 shows the effect of cluster strength on firms' VAT payments. Similar to model 2, it is based on fixed effects estimation because the Hausman test indicated random effects as inefficient (i.e., did not have minimal asymptotic variance). The Drukker/Wooldridge test did not indicate that autocorrelation was a problem in this model, so no autocorrelation control is included. The results are seemingly similar to those of model 2, although with somewhat higher explanatory power due to the omitted autocorrelation control. Also in this model, our cluster variable is significant, albeit at a somewhat lower level of significance ($P < 0.01$) than in the model on job creation. However, the magnitude of effects is strikingly similar; holding all other variables constant at their means, the marginal effect of own-cluster employment (in log form) on firms' VAT payments amounts to 0.094. A firm in a region with own-cluster employment of 2.50 will make taxation payments that are 9.4% higher than a similar firm located in a region with own-cluster employment of 1.50, or 22% higher with a 1 standard deviation increase in cluster strength. Also these effects are qualitatively identical if we estimate the model based on random effects or no effects. The Inverse Mills Ratio variable is significant, highlighting a selection effect for VAT payments—firms with a high likelihood of exit have lower turnover. Interestingly, the control variable for other-sector employment is now significant, suggesting that cluster congestion is not a problem (Beaudry and Swann 2001). Finally, the control variable for local universities is weakly significant, suggesting that firms situated in urban areas with research institutions tend to pay higher taxes.

Our last model, model 4, shows the effect of cluster strength on the mean salary levels of newly created jobs. Similar to model 2 on job creation, model 4 is based on fixed effects and includes a control for autocorrelation. The effects of the control variables are also very close to those of model 2, with the exception of human capital. The human capital variable is now significant and strongly positive, which is quite logical if we consider that the educational level within a firm should be associated with the level of salaries paid to employees. Also the control variable for regional house prices is significant, indicating that firms in more affluent areas need to pay higher wages. Most importantly, in this model of mean salary payments, the own-cluster employment variable is strongly significant. Looking at the marginal effects we find that a firm in a region with own-cluster employment of 2.50 will make pay salaries that are 10% higher than a similar firm located in a region with own-cluster employment of 1.50, or 24% higher with a 1 standard deviation increase in cluster strength. The effects are robust to models estimated by random or no effects. Throughout our models, the control variable for local universities remains insignificant. This could be attributed to the fact that the variable does not gauge the intensity and quality of research (e.g., Fritsch and Slavtchev 2007), but simply counts the presence of universities.

Finally, in unreported models we validated the analyses for all five cluster separately. With the exception of cluster four (Medical Equipment), which in Sweden is a quite small cluster, all findings were identical to reported models. Among the start-ups in Medical Equipment, same-cluster employees in the region contributed positively to survival ($P < 0.05$), but the positive effect on job creation is significant only at the 10% level. Further, for VAT payments and salary payments, the effects are even weaker, although the coefficients are in the expected direction. Also the models estimated only for start-ups in the Biopharmaceuticals cluster showed weaker results; however, all cluster variables were still significant at the 5% level. That only the smaller clusters showed weaker results indicates this is a problem of sample size and not a problem of pooling divergent industries.

5.1 The effect of alternative cluster measures

It has been pointed out throughout this paper that the inconclusive evidence of prior research of clusters on entrepreneurship and economic development might partly be attributed to methodological diversity and also differences in the geographical granularity of the data set used (Pe'er and Vertinsky 2006; Rocha 2004). Since there are several candidates in the empirical literature for the best way to identify and measure clusters, we chose the same-sector employment figure that we found was the most commonly used variable in prior studies and that also is in line with most of the theoretical effects suggested in the literature by the works of Marshall, Krugman, and Porter. However, given that

Table 5 Marginal effect of alternative cluster measures on firm survival and performance

Agglomeration measure	Regional base	Agglomeration base	Survival (%)	Job creation (%)	Tax payments (%)	Salary payments (%)
Counts (cluster size)	Labor market region	Employment	21.2	28.3	22.2	23.8
		Plants	23.2	34.9	34.5	19.1
	County	Employment	21.2	26.3	43.9	36.9
		Plants	5.2	28.5	42.7	42.3
	NUTS-2 region	Employment	17.4	28.6	31.4	57.2
		Plants	12.2	33.6	41.6	68.2
Quotients (specialization)	Labor market region	Employment	n/s	4.80	n/s	n/s
		Plants	2.3	n/s	12.30	6.70
	County	Employment	n/s	4.20	2.20	n/s
		Plants	5.0	n/s	10.10	16.50
	NUTS-2 region	Employment	n/s	n/s	n/s	9.40
		Plants	13.1	n/s	22.20	20.20

we had the choice to use other measures and also that we wanted to assess the findings on different geographical levels, we decided to assess the validity of our findings for competing measures of cluster and different geographical levels.

Table 5 summarizes the same four empirical models estimated as in Table 4, but with different measures of cluster and on different geographical levels. We show models based on counts (same-cluster number) of employees or plants, as well as models based on location quotients, i.e., the proportion of employees or plants in a specific industry in the region, relative to all employees/plants in that region. We also alternated our base for geographical level, labor market area, with county and NUTS-2 region.

Table 5 reveals several interesting patterns. First, our findings are quite robust across different ways of measuring clusters and also on different regional levels. Second, the magnitude of effects differs between measures and regional levels. Specifically, it seems that basing our measure of cluster on a higher regional level, such as counties (21 regions) or NUTS-2 regions (8 regions), indicates stronger effects than the base model showed for labor market region (87 regions).

To a certain extent, it is puzzling that measures based on location quotients of employees or plants reveals much weaker effects, sometimes not even statistically significant, compared to measures based on counts of employees or plants (but see Becchetti et al. 2007, for similar findings). In unreported tables we estimated the same empirical models with location quotients as cluster measure using both random and fixed effects. This revealed that random effects estimation showed statistical significance, but not fixed effects. There simply seems to be too little variation in quotients over time to be picked up by the fixed effects model. Since the Hausman test indicated that random effects based on location quotients are asymptotically inefficient, a tentative conclusion of Table 4 would be that, while location quotients are a good measures of identifying clusters, they are poorer measures for gauging the potential effect of variation in cluster strength on firm-level outcomes. Simply put, 10 biotech firms in a small town may stand out more than 15 firms in a big town, but the cluster benefits are nevertheless greater from 15 than from 10. An alternative conclusion is that we have failed to control for urbanization effects not captured by the controls for population density, local universities, and employment in other industries. This would then have biased our initial results for own-cluster employment. Yet, our control variables include the usual ways to measure urbanization effects, and our review of the empirical literature did not suggest the potential omission of some significant urbanization variable.

6 Discussion

In this paper we have investigated the effects of clusters on the survival and performance of new entrepreneurial firms. Using detailed firm-level data, we assessed all Swedish firms started during a 10-year period in five different industry groups and found evidence that a high concentration of own-cluster employment (in same industry and related industries) was related to better chances of survival, higher employment, higher tax payments, and higher salary payments. These effects are consistent for absolute agglomeration measures (counts), but weaker and inconsistent for relative agglomeration measures (location quotients). The strength of the effects vary depending on which geographical aggregation is chosen for the agglomeration measure. Our study contributes to the literatures on entrepreneurship and economic growth and agglomeration in economic geography. To the best of our knowledge, the study is the first of its kind to measure these outcomes at the level of the individual firm and not as regional aggregates.

These findings support previous research indicating that clusters do provide economic benefits not only for firms in general, but also for newly started entrepreneurial firms in particular. Although this study does not identify which mechanisms are producing these benefits, it does confirm that new firms in stronger clusters not only have higher survival rates, but also have higher economic performance in ways that have a direct impact on the regional economy. Several factors augment the external and internal validity of these conclusions, including the fact that 23 industries grouped in five different clusters were studied and the large and unbiased sample size of 4,397 firms started in the specified industries. The inclusion of fixed firm effects in our models effectively controls for many alternative factors that could have impacted our results. The findings of our study of five knowledge-intensive clusters can be contrasted to studies of other industries. Sorenson and Audia (2000) found in their study of the US footwear industry 1940–1989 that proximity to other footwear plants decreased the survival of footwear manufacturers. These divergent findings may indicate that clusters and agglomeration effects operate differently in knowledge-intensive versus capital-intensive industries. The fact that cluster effects were markedly weaker for start-ups in the smaller clusters (medical equipment and biotech/pharma) indicate that further research on larger clusters of this type is needed to substantiate the results for these industries.

The results from our analysis of different cluster measures echo those of Rosenthal and Strange (2001). They note that drivers behind agglomeration (such as knowledge spillovers and labor market effects) have different reach, some being strongest on the lower zip code levels, while others are more pronounced on the higher state level. The difference they find in the geographic reach of agglomeration *drivers*, we find in terms of economic *benefits* of agglomeration: some economic benefits are most pronounced on the lower labor market area level, while others are strongest on the higher NUTS2 level.

There are, however, also limitations to this study, primarily the fact that it is based only on Swedish data. Sweden is a small country where the industrial structure combines a large public sector with a relatively small, but highly international and productive private sector. The findings are therefore not necessarily generalizable to other countries. More research comparing regions, time periods, and especially different measurements will improve upon our attempt to establish consistencies in cluster measurement. In particular, studies using agglomeration measures based on NUTS-2 regions in other parts of Europe are certainly needed. Further, our evidence is limited to characteristics of the region/cluster and that of the firm. Including characteristics of the founding entrepreneurs, such as growth motivation or industry experience, is likely to reveal additional evidence on the determinants of new firm performance.

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Appendix 1. Inter-related industrial clusters

Cluster	Industry (5-level SIC equivalent)	Start-ups	Employees	Plants
Cluster 1: Telecom and consumer electronics	Manufacture of office machinery	25	1,379	53
	Manufacture of insulated wire and cable	41	4,804	81
	Manufacture of other electrical equipment	116	3,136	322
	Manufacture of television and radio	65	16,359	162
Cluster 2: Financial services	Other monetary intermediation	66	702	225
	Other credit granting	68	5,797	332
	Investment trust activities	79	1,213	237
	Unit trust activities	590	4,091	1,721
	Unit link insurance	16	991	60
	Other life insurance	17	3,586	140
	Non-life insurance	47	14,463	488
	Administration of financial markets	9	474	23
	Security brokerage and fund management	646	2,741	1,622
	Activities auxiliary to financial Insurance	331	2,516	708
	Management activities of holding companies	141	6,779	995
Cluster 3: Information technology	Manufacture of computers and IT equipment	172	2,271	349
	Manufacture of valves, tubes and electronics	176	6,018	410
	Publishing of software	1,291	13,233	2,869
Cluster 4: Medical equipment	Manufacture of medical/surgical equipment	170	7,293	507
	Manufacture of artificial teeth, dentures, etc.	268	1,817	725
Cluster 5: Pharmaceuticals	Preparation of biotechnical products	14	602	19
	Manufacture of pharmaceutical preparations	49	18,182	119
	Sum	4,397	118,447	12,167

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