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Seeds of regional structural change. The role of entrepreneurs and expanding firms in shaping local path dependencies

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ABSTRACT

This article studies path dependent regional structural change using a quantitative framework. Based on an inter-industry skill-relatedness indicator, the degree to which local skill-bases exist and force local economies onto a path-dependent development trajectory is studied. The main question is into which local industries new plants enter, while distinguishing between the plants of entrepreneurs and firms. Using a dataset on Swedish individuals and municipalities, it is found that entrepreneurs tend to reinforce established local industrial specializations, whereas new plants of already existing firms do less so. Moreover, outside actors deepen local economy's core specialization more than do local actors.

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1. Introduction

The capitalist system is characterized by continuous processes of creative destruction. Industries that were once relied upon to generate employment and wealth for a vast number of people in one generation will eventually go into decline. Such processes leave deep traces behind in local economies. For example, at the peak of its existence the Swedish shipbuilding industry employed about 39,000 persons and was a major employer in cities like Gothenburg, Malmö and Uddevalla. In the 1970s and 1980s, however, the industry was almost completely dismantled, forcing the affected regions to search for new growth opportunities or face decline and spiraling unemployment.

It is easy to find numerous examples of how local economies were affected by structural change that are similarly dramatic as the decline of the Swedish ship building industry. But unlike economic growth, which can be expressed in terms of employment or GDP growth, it is difficult to quantify structural change. As a consequence, economic geographers have typically relied on case study research when investigating these issues. This has resulted in a wide range of vivid illustrations of the nature and effects of path dependent structural change in declining regions (as in Grabher's 1993 study of the Ruhr area), as well as in emerging and successful regions (like Saxenian's 1994 work on Silicon Valley). Although this line of research has generated many important insights, its traditional focus on regions that underwent massive structural change makes it hard to assess how general its findings are.

In this study, we investigate the structural change and path dependent diversification processes in regions by employing a recently developed quantitative toolbox. Firms often search for regions with the right kind of specialized labor for their new activities. Therefore, arguably one of the most important assets of a local economy for structural renewal is the skills of its labor force. That is to say, the extent to which a region can attract new industries - or, the opportunities for local structural change - will strongly depend on the extent to which the local labor force of pre-existing industries can be reemployed in new but related economic activities. By means of a detailed investigation of cross-industry labor flows, the quantitative toolbox referred to above draws on a methodology that assesses to what extent the labor

forces of different industries are compatible. The degree to which, according to this methodology, two industries can draw on each other's labor force is subsequently called the skill-relatedness between these industries (Neffke and Svensson Henning 2009).

To investigate if and how these skill-relatedness structures of industries condition structural change in local economies, data on the new plants that were established in Swedish municipalities between 2004 and 2007 are analyzed. Using detailed information on the industries of these new local plants and about their skill-relatedness to the already existing industries in a municipality, we measure the extent to which the activities of new plants signal the possible beginnings of local structural change. In particular, the more unrelated the industries of new plants are to the existing industries in the municipality, the more radical the structural change that would take place if these new plants were to survive and grow. Moreover, the data also allow us to establish whether new plants were set up by existing firms, or by entrepreneurs. This is important information, because new plants of existing firms may have access to knowledge elsewhere in the firm that entrepreneurs lack. As a consequence, entrepreneurs might develop a greater reliance on local resources than new plants of existing firms. The dataset also provides information about the geographical origins of the entrepreneurs and existing firms that set up new plants. It is therefore possible to determine whether entrepreneurs and firms were previously active in the same municipality as the new plant, in the same region, or if they came from outside the new plant's region. We can thus distinguish between six different agents, and assess which agents reinforce present local specialization patterns most, and thereby which agents induce most local structural change.

The analyses show that local economies mostly consist of skill-related industries. This can be interpreted as indicating that, even at a very low level of spatial aggregation, there is a strong skill-cohesion among local industries. One may speculate that such clusters of related industries generate specific local skill-bases from which all local industries can benefit. Turning to the activities of new plants, these are found in industries that are closely related to the industries in which local economies specialize. New plants thus tend to reinforce local specialization patterns and the existing skill-base. Economic structures thus often shift only gradually, and local structural change is to a large extent path-dependent. However, the extent to which new plants shift local specialization patterns depends on the type of agent. Local cohesion is most strongly reinforced by entrepreneurs that come from outside the region. Next in line are regional entrepreneurs, and then local entrepreneurs. Quite surprisingly, plants of already existing firms induce potential structural change in local economies the most.

The paper is structured as follows. In section 2, we summarize the existing literature on structural change in regions, focusing on the path-dependent evolution of local economies according to regional branching processes. In section 3, we discuss skill-relatedness and its measurement. Section 4 describes the data, and provides information about the Swedish economy and its geography. Section 5 contains the empirical analysis of structural change in Swedish municipalities. Section 6 discusses the results, concludes and suggests areas for new research.

2. Path dependence and the different agents of local structural change

Path dependence in geography

An important conjecture underlying this article is that structural change is not random, but takes the form of a *path dependent* process. We expect that the industrial orientation of a region, that is, its specialization in a particular set of industries, usually shifts gradually and incrementally over time. Moreover, the direction of structural change depends on the present industrial structure of the local economy.¹

Research on path dependence was pioneered by David (1985) and Arthur (1989, 1994). According to David (2007, p. 92), a path dependent process is “[a] dynamical process whose evolution is governed by its own history ...”. Most of the early work of Arthur and David focused on how technological standards got established. The most famous example is probably the QWERTY keyboard layout. Although technologically and ergonomically inferior, the QWERTY design managed to survive due to a combination of a small, yet early, lead over competing designs, and complementarities between the physical hardware of typewriters and the skills acquired by typists. A general theme in this path dependency literature is that “history matters”, and that in the presence of self-reinforcing processes arising from scale economies and network effects, seemingly minor events can have a major impact on the end state a system will reach. However, emphasizing the process rather than the end states, the works by David also highlight the irreversibility of this process, and that this has profound consequences

¹ This is not to say that regions can never experience very radical change. However, such radical change should be considered exceptional rather than the norm.

for the ways in which economies develop along historical paths (Bassanini and Dosi 2001, Martin and Sunley 2006).

Given the traditional focus of the discipline on regional contextualities, it is not surprising that path dependence and the concomitant phenomenon of “lock-in” are quickly gaining ground in contemporary economic geography. Arthur (1994) himself used path dependence to explain how, as long as self-reinforcing agglomeration effects are sufficiently strong, random events that take place early in an industry’s evolution can lock the industry into a specific region. Krugman (1991) gives the example of carpet manufacturing in Dalton to argue that economic clustering can often be traced back to essentially an historical accident that was subsequently amplified by the workings of localization economies.

In contrast to the mainly mathematical approaches of Arthur and Krugman, economic geographers have so far tended to use path dependence and lock-in in vivid narratives stressing the complexities behind the emergence and evolution of local industries and clusters. In their elaborate overview of path dependence research in economic geography, Martin and Sunley (2006, p. 429) conclude that albeit some qualifications “the path dependence perspective has much to offer economic geographers”, and identify three main areas that research has focused on so far. First, there is the wide range of case studies alluded to above, which tend to focus either on regional success stories (e.g. Cooke and Morgan 1998, Kenney and von Burg 2001), processes of dramatic regional decline (e.g. Grabher 1993, Eich-Born and Hassink 2005, Hassink 2007), or studies about how regional development paths are composed of complex industry trajectories (Bathelt and Boggs, 2003). Second, a group of scholars have studied the spatial evolution of a given industry across different locations. Examples of this approach are the analyses on spatial aspects of industry life cycles by Klepper (2002) and Boschma and Wenting (2007). A third line of research is exemplified by Rigby and Essletzbichler (1997), who show that industries use local technological regimes that are persistently different across regions.

Notwithstanding these important contributions, Martin and Sunley (2006, p. 411) argue that there is a fourth and “potentially most interesting test of the path dependence idea” in economic geography, which has so far remained empirically under-explored. This research agenda focuses on how a regional economy evolves as whole, and whether this evolution is path dependent. It is precisely here that the present study aims to make its contribution.

Regional structural change and path dependency

At the level of the region as a whole, path-dependent processes are very complex, as development paths of different local industries may interlock among each other and with the evolution of local institutions. Consequently, the topic may not seem to lend itself easily to quantification and it is not surprising that such phenomena have until recently been the exclusive domain of case studies.² Although these studies often feature interesting findings, it is difficult to assess their generality. This suggests that a more quantitative approach is needed to complement the qualitative research on the topic. The main impediment to such a quantitative agenda is that the path dependent development of a local economy is fundamentally qualitative in nature.³ That is, local structural change is, in the first place, not concerned with readily quantifiable entities like employment or GDP, but with changes in the industrial composition of regional economies. In other words, more important than *how much* is produced in a region, is *what* is produced there. In fact, this article will argue that one of the most important prerequisites for understanding local structural change is knowing exactly which industries are present in a region, and how these industries are related to other industries in the wider economy.

A promising attempt to study how the relatedness among industries affects regional development can be found in Frenken et al.'s (2007) introduction of the related variety concept. The rationale behind related variety is that regional economies develop according to an evolutionary branching process (Frenken and Boschma 2007, Boschma and Frenken 2009). Accordingly, regions build up a local resource base that fits the requirements of its industries. For instance, a strong presence of local industries often creates specialized pools of labor and suitable (knowledge) infrastructure. But industries are of course not isolated entities: local resources are hardly ever completely industry specific, but often benefit a number of related industries. Evidence for this can, for example, be found, for example, in Neffke et al. (2008). They show that survival chances of manufacturing plants rise when plants are surrounded by a large number of plants, not in the same industry, but rather in related industries. But local resources are not only important for the already existing industries or firms in the region. On the contrary, as argued by Martin (2010), it is likely that new activities also depend on these local resource bases and are therefore developed in industries that are related to the region's pre-existing industries:

² Although the author never explicitly uses the term "path dependence", Glaeser's work on the long-term evolution of the economies of Boston (Glaeser 2005) and New York (Glaeser 2007) can also be thought of as examples of such studies.

³ This was of course emphasized by the early Schumpeter at the level of national economies. Later, the argument found its way into the evolutionary economic geography approach (Boschma and Frenken 2009).

“The emergence of a new local industry may not be due to ‘chance’ or ‘historical accident’ but stimulated or enabled – at least in part – by the pre-existing resources, competences, skills and experiences inherited from previous local paths and patterns of economic development.” (Martin 2010, p. 29)

Consequently, structural change will be predominantly gradual, in the sense that new activities often are closely connected to old. New plants will be set up in industries that are closely related to the region’s already existing core activities. Such a pattern reflects the path dependent dynamics of regional structural change. Indeed, the industrial past of the region matters for its future development. Moreover, the process of structural change is most likely irreversible.

However, just how closely the activities in new plants will be related to the pre-existing local industries (i.e. how path dependent the process actually is), may depend on the agent that sets up the plant. For instance, Henderson (2003) and Neffke et al. (2008) show that plants belonging to larger corporations draw different, and often fewer, benefits from the local economic environment than stand alone plants. Moreover, contrary to commonly held beliefs, Staber (2005) argues that entrepreneurs often reinforce regional industrial structures rather than transforming them due to social conformity, positive experiences from earlier efforts, imitation of existing practices and technologies, and introvert social networks. This means that instead of serving as agents of radical change, entrepreneurs may often deepen established industrial structures. The degree to which new plants signal local structural change may thus depend on whether they are set up by already existing firms, or by entrepreneurs. Furthermore, it may matter where, in terms of geographical location, an agent was previously active. Entrepreneurs, for instance, often start their businesses in their own region (Malecki, 1994) and this preference may override efforts to finding the perfect location for their activities. The entrepreneurs that do leave their region may therefore be rather atypical and behave in different ways than entrepreneurs that stay close to home. Firms, on the other hand, may use internal resources instead of drawing on the local resource base. Therefore, they may be less affected by pre-existing industries in a region than entrepreneurs. The capacity of a region to transform may thus critically depend on which type of agent is responsible for new economic activities in that particular region.

Quantifying structural change

To investigate these issues, there is a need to quantify structural change. This requires attaching a numerical value to the diversification of a local economy into a particular industry. For instance, a diversification into motor cycle manufacturing in Gothenburg (which, home to car manufacturer Volvo's head quarters, is Sweden's largest automotive center), would cause little structural change as compared to a similar diversification in many other regions in Sweden. In order to assess *how much* structural change is involved in the local diversification of a *particular region* into a *particular industry*, a numerical value for the degree to which the new industry differs from the existing industries in the region has to be calculated. In positive terms, it is necessary to establish the degree to which industries are related.

Such measures are presently becoming rapidly available. For instance, Hidalgo et al. (2007) study national export portfolios in detail to arrive at what they call product space, a network depicting relatedness linkages among product categories. Teece et al. (1994) and Bryce and Winter (2009) derive a similar network for industries, based on corporate portfolios. Such relatedness also matters for structural change. Hidalgo et al. (2007) show that, at the national level, opportunities for structural change depend on a country's present export portfolio, and how this portfolio is connected to new product varieties in terms of relatedness. The authors find that radical reorientations of a country's industrial specialization occur very infrequently. At the regional level, Neffke et al. (2009) use a relatedness indicator based on plant portfolio data to study structural transformation of Swedish regions. They find that also regional structural change is a gradual process, with new activities being closely linked to old. While in line with the arguments of the present article, the latter two studies are limited to the manufacturing sector and they do not differentiate among different agents that may drive this structural change.

In what follows, we will introduce a new index that quantifies the skill-relatedness among industries. Contrary to other types of relatedness measures, the index used here is measured economy-wide, including manufacturing as well as all types of services and utilities. Another attractive feature of skill-relatedness is its focus on the relatedness between industries in terms of the compatibility of their labor forces. In the present knowledge economy, the knowledge and skills of the local labor force are often thought to be the most important resources of a region (Florida 2002, Glaeser 2005).

3. Skill-relatedness

In their article on related variety, Frenken et al. (2007) use what is perhaps the most frequently employed method to assess inter-industry relatedness by drawing on the hierarchical structure of the standard industrial classification system. Standard industrial classification systems categorize economic activities into a nested structure of progressively finer industrial classes. In the European NACE classification system, industry codes consist of up to 5 digits. The NACE codes have national counterparts, for which the first four digits are the same across countries. Even at this four-digit level the classification is rather detailed. The Swedish SNI02 implementation of the NACE system distinguishes, for example, between “0123: Farming of swine” and “0121: Farming of cattle, dairy farming”. Based on the classification codes, one would interpret the fact that swine and cattle farming share three out of four digits as an indication that these are strongly related. Contrary to what would be expected however, swine farming is classified as completely unrelated to, for instance, “8520: Veterinary activities” and “1511: Production and preserving of meat”. Classification based relatedness therefore seems to overlook important intuitive linkages among industries. Moreover, industries that we would typically regard as being unrelated, such as “7411: Legal activities” and “7470: Industrial cleaning” are classified as related through two-digit class: “74: Other business activities”.

Because of these drawbacks of industrial classification systems, this article proposes the use of a different indicator of industry relatedness. Neffke and Svensson Henning (2009) develop a measure that captures skill-relatedness among all over 400 four-digit industries.⁴ This relatedness indicator has an economy-wide coverage, and sheds light on cross-industry linkages at a very detailed level of disaggregation.⁵

Measurement

The skill-relatedness measure in Neffke and Svensson Henning (2009) is based on cross-industry labor flows. The basic rationale for using labor flows as an indicator of skill-relatedness is found in recent labor economics research (Ingram and Neumann 2006, Poletaev and Robinson 2008, Gathmann and Schoenberg 2010). This literature shows that people build up human capital, partly through formal education but partly also through learning-by-doing processes, that is specific to their job. This job-

⁴ These are all industries with over 250 employees in the Swedish economy.

⁵ By comparison, input-output based measures cover all industries in the economy, but only at the two-digit level. The co-occurrence relatedness measures in Teece et al. (1994), Hidalgo et al. (2007), Bryce and Winter (2009) and Neffke and Svensson Henning (2009) all do not cover services.

specific human capital will often lose its value when the individual changes to a new job. Job switchers will try to minimize this destruction of the value of their human capital by predominantly moving to industries in which their old skills are still valued. As a result, cross-industry labor flows should reflect the degree to which different industries value the same skills.

However, contrary to staff with strong and specialized skills, labor flows of low-skilled individuals or of individuals whose jobs demand more generic skills which can be used in virtually any industry, will be relatively insensitive to the skill-relatedness between industries. Flows that are generated if such individuals switch jobs are therefore left out from the relatedness calculations, and the analysis concentrates on the labor moves of what one might call qualified staff. Furthermore, total labor flows between industries do not just depend on the skill-relatedness of industries. Larger industries will generate larger labor flows, and industries with high average wages will *ceteris paribus* attract more employees than industries that pay low wages. Raw data on labor flows across industries must thus be compared to a benchmark that reflects the overall sizes of and wages in the industries. In Neffke and Svensson Henning (2009) this is done by calculating an expected labor flow of qualified staff between industries by means of regression analysis, using the sizes of the industries and their average wages as predictors. Next, the skill-relatedness between industry i and j is calculated as the ratio of observed versus expected flows:

$$(1) \quad SR_{ij} = \frac{F_{ij}}{\hat{F}_{ij}}$$

where F_{ij} represents the observed flow from i to j and \hat{F}_{ij} the predicted flow based on the above mentioned regression analysis.⁶ An SR -value above 1 indicates that there is an excess flow of qualified labor between industries, which the authors interpret as evidence for relatedness between these industries.

Using data on labor market affiliations of all about 9 million inhabitants of Sweden during 2004-2007, Neffke and Svensson Henning calculate skill-relatedness for about 181,000 industry combinations. Here, we repeat the procedure described in Neffke and Svensson Henning (2009). But as our aim is to study how new plants induce local structural change, using the employment flows that involve new plants

⁶ Neffke and Svensson Henning (2009) use a zero inflated negative binomial regression model for estimations. We refer the reader to this paper for further details.

might result in circular reasoning. In this article therefore, the original dataset is restricted by leaving out all employees that were at any point employed in a new plant, that is, a plant that did not exist in 2004. To illustrate the procedure, take the example of swine farming and veterinary activities. In the period 2004-2007 there were some 725 swine farmers in Sweden and 1,750 people working in veterinary activities each year. They earned on average around 22,000 EUR and 32,500 EUR a year. Based on these numbers, and the parameter estimates obtained from the regression of observed flows on employment and wage data, the expected labor flow from swine farming to veterinary activities would be 0.13 employees (less than one individual). In reality, however, we observe a total labor flow of 3 individuals. Therefore, the skill-relatedness between swine farming and veterinary activities is $\frac{3}{0.13}$ or around 23.⁷

Table 1 lists the top 10 related industries in the Swedish economy (leaving out the smallest industries). Many of the industries listed in this table are also to some degree close to each other in the classification system. However, as in the example of newspaper publishing and advertising, some industries are also classified into completely different economic sectors.

- Table 1 about here -

To give an overall impression of the skill-relatedness linkages in the economy, Figure 1 displays skill-relatedness in a network graph, which shall subsequently be referred to as “industry space”.⁸ The nodes of this network are four-digit industries, and the lines between them represent skill-relatedness linkages. The shapes and colors of the nodes distinguish between the broad two-digit classes these industries belong to. Roughly, the more close industries are to one another in the graph, the more closely they are skill-related. The graph shows that services and manufacturing industries are indeed mostly concentrated in different parts of industry space. Moreover, subsectors like finance, agriculture and construction all consist of closely skill-related industries. However, there are also many exceptions to this regular pattern. For instance, some wholesale and retail industries are closely related to their manufacturing counterparts. Business services are scattered around the network and are connected to a number of manufacturing industries. Many such linkages would have been overlooked when only using the industrial classification system.

⁷ With a p-value of 0.0003, this is significantly larger than 1 at any conventional confidence level and therefore indicates strong relatedness. For the construction of confidence intervals on the SR index, the reader is referred to the article by Neffke and Svensson Henning (2009).

⁸ This graph was produced using the NetDraw software program (Borgatti 2002). We use the term “industry space” in analogy to the product space in Hidalgo et al. (2007).

- Figure 1 about here -

4. Data and the Swedish economy and its municipalities

The main cities in Sweden are Stockholm (1.25 million inhabitants including the municipalities in the wider metropolitan area), Gothenburg (910,000 inhabitants) and Malmö (630,000 inhabitants). The geographical distribution of the Swedish population is very skewed. Sweden has a 25% larger surface area than Germany, and the distance between the southern-most and northern-most points of Sweden is comparable to the distance between Malmö and Naples, (about 1900 kilometers by road). The vast majority of Sweden's population of around 9 million people lives in and south of Stockholm. This means that the north of Sweden is left with vast and scarcely populated areas compared to the much more densely populated south. Swedish income per capita usually ranks among the top 15 countries in the world. The economy of Sweden was for a long time based on the success of traditional manufacturing industries, for example car making, shipbuilding and heavy machinery industries (Schön 2000, Svensson Henning 2009), and natural resource based industries, such as wood and steel industries. As other advanced economies, Sweden has increasingly moved towards an economy dominated by service sectors (Lundquist et al. 2008). Today, producer service industries employ almost as many people as all manufacturing industries together. Moreover, about 30% of all employees are working in the public sector.

The unit of analysis in this paper is the evolution of the economies of municipalities. Municipalities are often thought to be too small as a spatial unit of analysis. However, in many countries, municipalities have more policy making powers than mid-level authorities, such as regions and provinces. Moreover, a large proportion of government expenditures is undertaken by municipalities. In the Swedish case, municipality-specific taxes also represent the major part of the country's income tax. Furthermore, the municipality is the level of government that most directly faces the problems of unemployment and labor market reintegration. Sweden has 290 municipalities, ranging in size from Stockholm (830,000 inhabitants) to Bjurholm (2,500 inhabitants). In the empirical section, we differentiate among new plants that were set up by agents from the same municipality, from the same region and from outside the region. In this study, a region refers to one of the 75 labor market areas used by Statistics Sweden. A labor market area normally consists of several municipalities.

The dataset used was made available by Statistics Sweden. It covers all little over 9 million individuals registered in Sweden in the years 2004 to 2007. Of these, around 4.5 million are employed on the labor market. In these data, we can follow individual plants and firms through time, regardless of changes in ownership or legal status.⁹

Through firm identifiers, we can determine for each new plant whether or not it was set up by an already existing firm. The spatial origin for new plants of such expanding firms is defined as the municipality in which the firm had most employees in the year previous to the founding year of the new plant. For all new plants that do not belong to a larger firm, we identify one person as the entrepreneur. This is taken to be the employee in the plant that earns the highest income from a private business.¹⁰ The spatial origin of an entrepreneur's new plant is determined by the municipality of the plant where he or she worked in the year before.

5. Industrial structure and evolution of local economies

Terminology and unit of analysis

The empirical analyses in this section focus on the local industry. A local industry is defined as an industry in a specific municipality. For instance, shipbuilding-in-Gothenburg is a local industry, or restaurants-in-Stockholm. In total, there are 413 industries and 290 municipalities, and consequently we can distinguish between $413 \times 290 = 120,930$ local industries. Not all local industries will in fact exist. These industries will be referred to as *non-existing*. For instance, in the municipality of Åmål there are no people working in a cinema. As a consequence, the local cinema-in-Åmål industry is non-existing. Analogously, we will call industries that do have employment in a region "existing local industries."

To characterize the structural composition of a local economy, we use the term *local portfolio*. A municipality's local portfolio of industries consists of all industries that have a location quotient that exceeds one. In other words, the local portfolio consists of all industries for which the share of the

⁹ The indicator used to do this is described by Andersson and Arvidsson (2006) and was designed by Statistics Sweden. It is considered to be highly reliable.

¹⁰ Formally, this is the income from gainful activities that are carried out professionally and independently, or "inkomst från näringsverksamhet". We regard this as the best indicator in our data to decide which person is the principal entrepreneur in the newly established plant. Even though an individual could derive large incomes of this type from other plants than the plant that employs the individual, we do not think such unlikely situations will seriously affect our results, considering the ways in which we identify the entrepreneur.

overall employment in the municipality is larger than the industry's share of the total employment in the country as a whole. That is, a municipality m 's portfolio, PF_m , is defined as:¹¹

$$(2) \quad PF_m = \left\{ i \mid \frac{emp_{m,i} \ emp_m}{emp_i \ emp} > 1 \right\}, \text{ where:}$$

$emp_{m,i}$:	employment in municipality m and industry i
emp_m :	sum of all employment in municipality m
emp_i :	sum of industry i 's employment in the whole of Sweden
emp :	sum of all employment in Sweden

New plants give rise to new employment and thus lead to an expansion of the local economy.¹² We will say that a local industry in which one or more plants are set up experiences an *expansion event*. In other words, expansion is not defined at the plant level, but at the level of the local industry. In most of the analyses, we are not interested in the number of new plants or employment involved in the event but in whether or not it took place at all.

Our main interest is to find out in which local industries such expansion and diversification events take place. In particular, we would like to know if the frequency of expansion and diversification events depends on how closely skill-related a local industry is to the local portfolio. From the skill-relatedness measure it can be derived how related two industries are to one another. However, it is not yet clear how skill-related an industry is to an entire basket of industries. For this purpose, we define a local industry i 's skill-proximity¹³ to the local portfolio of municipality m , $SP_{i,m}$, as the number of industries in the portfolio of m to which industry i is closely related. At what value of skill-relatedness one should call two industries closely related is to some extent arbitrary. A threshold value of 1 would be a natural choice, as that level would imply excessive labor flows. However, in this article, a value is used that is slightly smaller, 0.9286. At this value, the number of industry combinations that are considered to be closely related equals the number of industry combinations for which the first digit in the classification

¹¹ Alternatively, one can define the portfolio of m as all local industries that are present, i.e., have an employment above zero. Our analyses are not sensitive to such a change in definition.

¹² At the same time, downsizing plants or plants that even shut down will lead to a contraction of the local economy. However, in this paper the focus is on new plants and the growth, decline and closure of existing plants are left for future research.

¹³ The relatedness index is a-spatial but it is quite natural to use spatial metaphors, like industry space, to discuss the relatedness linkages between industries. In order to avoid confusion with geographical distances and locations, we will use the prefix "skill-", as in skill-proximity, if we refer to distances in industry space.

codes is the same.¹⁴ This will facilitate comparisons between analyses based on skill-relatedness and analyses that use the classification system to assess relatedness between industries. Equation (3) formally defines skill-proximity:

$$(3) \quad SP_{i,m} = \sum_{j \neq i} I(j \in PF_m \wedge SR_{j,i} > 0.9286), \text{ where:}$$

$I(\cdot)$ is an indicator function that evaluates to one if its argument is true. Figure 2 illustrates the procedure for a simplified industry space. The dark circles are part of municipality m 's portfolio, whereas the white circles represent industries that are not. Two circles are connected by a line if the corresponding industries have a skill-relatedness over the above defined threshold. Local industry 2, which is an existing local industry, strongly related to three of the industries in m 's portfolio, giving it a closeness value of $SP_{2,m} = 3$. Similarly, the non-existing local industry 20 has a closeness value of $SP_{20,m} = 2$. We can repeat these calculations for all, existing and non-existing, local industries. However, as large municipalities have many local industries, the skill-proximity of local industries to such municipalities will also be large. In order to prevent size effects from distorting the analyses, we divide all skill-proximity values by the total number of industries in the local portfolio so they express the percentage of industries in the local portfolio that are closely skill-related to the local industry at hand. To summarize, skill-relatedness is defined between two industries, whereas skill-proximity is defined between a local industry and a portfolio of industries.

- Figure 2 about here -

New plants and new plant employment

Before studying the importance of skill-relatedness and skill-proximity in the local economy, it is informative to first have a look at Table 2, which contains information on the new plants that were established in Sweden in the period we investigate.

- Table 2 about here -

New plants accounted for over 400,000 employees in this period. This amounts to a little less than 1 in 10 employees in Sweden. If we now focus on their owners, we find that new plants belonging to

¹⁴ Over 85% of all industry combinations do not share the same first digit.

entrepreneurs outnumber the new plants owned by existing firms by 12.8 to 1. Within the group of entrepreneurs, local entrepreneurs are by far the most numerous, whereas existing firms come about as often from the same municipality as where the new plant was founded as from outside the plant's labor market area. Firms apparently either choose to set up their new plants close to home, or in an entirely different labor market area. The fact that existing firms are vastly outnumbered by entrepreneurs when it comes to the *number* of new plants in the economy does however not mean that they are unimportant. As shown in Table 2, their new plants are about five times as large as those of entrepreneurs.

Skill coherence of local industry portfolios

Figure 3 shows the average skill-proximity to the local portfolio of different groupings of local industries. We expect that local economies exhibit a high degree of coherence in the sense that municipalities will mostly specialize in sets of industries that share the same broad skill-base and are thus skill-related. Panel A of Figure 3 shows the average skill-proximity of existing local industries in the upper solid line. On average, existing local industries are closely skill-related to some 20% of all industries in the local portfolio. In itself, this number is not very informative. As a comparison, the lower solid line shows the skill-proximity of non-existing local industries, that is, industries that are not present in the municipality, to the portfolio. This group of local industries is closely related to only 11% of the local portfolio. The difference between both groups is statistically highly significant. The local economy of a municipality thus appears indeed often to be organized around a set of industries¹⁵ that share the same labor force. In this sense, local economies could therefore be called skill-coherent.

- Figure 3 about here -

The dashed line shows the average skill-proximity to the local portfolio of local industries in which a new plant was set up. That is, it shows the average skill-proximity of local industries that experienced an expansion event. These local industries are even closer to the portfolio than many of the municipality's existing industries. New plants are often set up in industries that belong to the local portfolio.¹⁶

¹⁵ Please note that it is possible that a municipality's economy consists of a number of different sets of industries that are each organized around their own specific skill-bases. Therefore, often there will be more than one skill-base in a municipality.

¹⁶ Please note that not all existing industries in a municipality are a part of the municipality's portfolio. Only industries that are over-represented compared to the national average are.

Moreover, they often belong to industries in what could be called a skill-core of the portfolio, that is, a set of industries in the portfolio that are strongly connected among each other. Consequently, new plants tend to reinforce existing skill-core(s) and further entrench current industrial specialization(s) of a municipality.

Panel B of Figure 3, repeats the skill-proximity of existing and non-existing local industries as reference points but further analyzes local industries that experienced an expansion event by differentiating between the agents that caused the expansion event. This allows us to assess which of our six agents¹⁷ set up their plants in local industries that are most closely related to the local portfolio. The dotted lines reflect average skill-proximities for local industries that experienced expansion events due to plant openings by entrepreneurs and the dashed lines refer to the expansion events caused by existing firms. If the lines are marked by squares, the plants were set up by local agents. Triangles refer to regional agents and diamonds refer to agents from outside the region.

Entrepreneurs predominantly set up their plants in local industries that are very close to the local portfolio. This tendency is strongest for entrepreneurs that come from farthest away. By comparison, the plants of local entrepreneurs are least skill-proximate to the local portfolio. Also firms set up their new plants in local industries that are close to the skill-core(s) of a municipality but in general to a lesser degree than do entrepreneurs. As was the case for entrepreneurs, also firms that come from farther away tend to set up plants in local industries that are very skill-proximate to the local portfolio. In 2006, the new plants from firms from outside the region are even more skill-proximate to the portfolio than those of local entrepreneurs. Averaged across all years however, the difference between both types of plants is, with a p-value of 4.9%, statistically hardly significant. Plants of local firms and plants of regional firms are less skill-proximate.¹⁸

As a first conclusion, we could thus say that the new plants of entrepreneurs tend to reinforce a local economy's specialization in its current skill-core(s) more than the new plants of already existing firms. A possible reason for this is that entrepreneurs strongly depend on the local resource base. Plants belonging to a larger firm may instead draw on firm-internal resources and skills. As a consequence, the specialization of the local environment may be of less importance to them. Our second observation is that the more geographically distant the origins of the entrepreneurs and firms, the more closely their

¹⁷ That is, local entrepreneurs, regional entrepreneurs, entrepreneurs from outside the region, local firms, regional firms, and firms from outside the region.

¹⁸ The differences between the means for local and regional firm expansions are not significantly different from one another. For all other pair-wise combinations of the six agent types differences are always highly significant, with p-values for the test on equality of means never exceeding 1.8%.

plants fit into the existing local skill-base(s). Therefore, outsiders often tend to reinforce local specializations. This may seem counter-intuitive. However, firms and entrepreneurs that choose to leave their home region often have to make sacrifices for this. In return, they may want to locate in the region that best meets their requirements in terms of locally available skill-bases. In what follows, we will explore these patterns in greater detail.

Skill-proximity and expansion probabilities

Another way to assess the importance of skill-relatedness is studying the probability that a local industry experiences an expansion event. This probability should be larger the more skill-related industries are found in the local portfolio. Figure 4 shows how estimated probabilities of expansion events in local industries differ for different degrees of skill-proximity. The horizontal axis contains the ten deciles of the distribution of skill-proximity values. That is, the first category contains the expansion probability for local industries that belong to the bottom 10% in terms of skill-proximity to their local portfolio and the last category contains the top 10% skill-proximate local industries. In the upper panels, the vertical axis shows the estimated probability that an expansion event takes place. That is, it shows the relative frequencies with which expansion events are observed in different skill-proximity deciles. In the lower panels, the vertical axis expresses these values relative to the value of the fifth, middle decile on a log scale to stress changes between deciles.

- Figure 4 about here -

The absolute probability of an expansion event caused by activities of existing firms is much lower than for those that are due to entrepreneurial activity. The reason is that entrepreneurs set up vastly more plants than existing firms as shown in Table 2. We are however more interested in expansion probabilities increase as we move to higher deciles. Clearly, the probability that a new plant is set up in a local industry depends strongly on how skill-proximate the industry is to the local portfolio. If we do not distinguish by agent, such an event is 18.3 times as likely in the highest decile compared to the lowest decile. Existing firms and entrepreneurs are very similar in this respect. With a factor of 20.7, the increase for firms is only slightly higher than for entrepreneurs (a factor of 17.0).

Figure 4B differentiates entrepreneurs by geographical origin. Given the paucity of new plants of existing firms, we do not show more detailed results for this agent type. First, in absolute terms, expansion events are more likely to involve local entrepreneurial activities. However, with a 33.6 and 33.9 times

increase between the lowest and highest decile, the expansion probabilities rise much faster for regional entrepreneurs and entrepreneurs from outside the region, than for local entrepreneurs (20.6). This confirms our earlier finding that entrepreneurs that leave their home region are particularly keen on locating in regions with the right skill-base for their activities.

Statistical significance of results: regression analyses

Thus far all analyses were bi-variate. We will now discuss some regression analyses in order to show that our findings are also robust to adding control variables. The control variables we use are the total employment of the industry in Sweden and the total employment in the local economy. Both variables have been log-transformed. Moreover, we also constructed a variable that measures the proximity of local industries to the local portfolio, not in terms of skill-relatedness, but in terms of the relatedness suggested by the industrial classification system. That is, we count the number of industries in the local portfolio that share the same first digit as the local industry at hand.

Table 3 reports the outcomes of logit regressions for the event that a local industry experiences an expansion event by any of the six agent types. Column (1) only contains the skill-proximity of the local industry to the portfolio.¹⁹ The coefficient is highly significant and, at median values, implies a 1 percentage point increase in expansion probability for each extra unit of skill-proximity. Given a standard deviation of skill-proximity of around 12.5, this is substantial. Column (2) repeats the regression, but now uses the classification-based relatedness measure to calculate local industries' proximity to their local portfolios. Although also this variable is highly significant, the effect size is much lower. In fact the marginal effect, again evaluated at median values, is only about one third of the marginal effect reported in Column (1). Column (3) directly compares the two variables. The coefficient for the skill-relatedness based measure hardly changes. However, the significance of the classification based variable's coefficient drops substantially and the effect even turns negative. This shows that when establishing new plants, being skill-related to many industries in the local portfolio matters far more than belonging to the same broad industrial class. Finally, column (4) adds controls for the size of the local economy and for the size of the industry at a national level. The classification-based proximity variable turns positive again, but remains very small. The skill-relatedness index drops to about half its previous size, but remains substantial and statistically highly significant. This shows that the earlier

¹⁹ As we will control for the sizes of the industry and the local economy, we use the absolute skill-proximity values here, without dividing them by the total number of industries in the local portfolio.

presented bi-variate findings cannot solely be attributed to differences in the sizes of industries and local economies.

Using a multinomial logit regression, we can also investigate whether the finding that different agents behave differently when it comes to setting up new plants is robust to including controls. In appendix A, we show the results of this analysis. If anything, the differences are even more pronounced than in our bi-variate analyses. In general, to existing firms, skill-proximity to the portfolio matters less than to entrepreneurs. Moreover, the farther away the agents come from, the more importance they give to skill-proximity.²⁰

Economic implications of skill-relatedness : new plant employment

The analyses so far have shown that there is the skill-relatedness among industries affects local economies is a way that is statistically highly significant. However, we have not yet discussed the economic implications of skill-relatedness and skill-proximity. To this end, Figure 5 shows the employment that is created by the establishment of new plants in local industries belonging to different skill-proximity deciles.

- Figure 5 about here -

The new plant employment created in local industries in the highest skill-proximity decile is almost 190,000 employees. These local industries account thus for about half of the overall new plant employment in the Swedish economy and these new plants strongly reinforce current local skill-bases. By comparison, the new plants in the industries of the lowest skill-proximity decile provide jobs to only 2,746 people. This raises the question how much structural change can actually be expected to result from new plants. In fact, some new plant employment does arise in local industries that are less closely skill-related to the existing activities in the local economy. The bottom half of the proximity deciles, for instance, consist of local industries that are relatively far from the local portfolio in terms of skill-proximity. The new plant employment in the lowest five skill-proximity deciles is generated for about 36% by local entrepreneurs and for 17% by local firms. On this account, provided that these new plants

²⁰ The differences between the parameter estimates of skill-proximity for different agents are significant at the 1% level in all but two cases. First, entrepreneurs from outside the region are similarly affected by skill-proximity as regional entrepreneurs. Second, the effect of skill-proximity is about equally large for regional firms as for local entrepreneurs.

and their local industries will keep growing, local entrepreneurs and local firms should be considered to be the prime agents of structural change in a region.

- Table 3 about here -

6. Conclusion

Structural change has drastic consequences for the economic fortunes of regions. In recent years, economic geographers have started investigating the role of path dependency in such regional structural change. Whilst most enquiries into regional path dependence so far have a case-study orientation, this article aimed at studying the degree of local structural change in a quantitative manner. To this end, an index was used that measures the degree to which two industries are skill-related in the sense that they draw on largely the same workforce.

The empirical analyses reported in the article investigated whether this skill-relatedness is reflected in the industrial composition of Swedish municipalities. The local industrial portfolios of these municipalities are indeed to large extent skill-coherent. This suggests that even at a very low scale of spatial aggregation, regions build up local skill-bases that attract industries with human capital needs that are similar to the region's current core industries. Moreover, when focusing on changes in the industrial composition of a region caused by the establishment of new plants, skill-relatedness has different effects for different types of agents. In particular, entrepreneurs are more likely to set up plants in industries that are skill-related to most of the industries in which a municipality specializes than are existing firms. Moreover, the farther away the municipalities of the previous activities of firms and entrepreneurs are the more often do they set up plants in industries that are very closely skill-related to the local economies' industrial specializations.

Overall, entrepreneurs generate more new plant employment than do existing firms although existing firms often set up substantially larger plants. Focusing on the potential for structural change in a new plant, local entrepreneurs and, albeit to a lesser extent, local firms are most important for sowing the seeds for new specializations to arise in a local economy. Their new plants account for the largest share of new plant employment in industries that are presently not very closely skill-related to a municipality's portfolio of core industries.

The findings in this article may be of considerable value to local policy makers. Depending on whether policy is aimed at reinforcing current industrial structure or rather diversifying away from it, different

economic agents are usually involved. Entrepreneurs and firms from outside the region are most likely to reinforce existing specializations in the industries that constitute the local economy's skill-cores, whereas local entrepreneurs and local firms are more likely to induce structural change. However, our current analyses do not allow us to establish which agents are most important in the long run. For this purpose, survival rates of plants of different agents and at different degrees of skill-proximity to the local economy's core activities should be investigated. Moreover, structural change will also take place because existing plants grow or decline and sometimes completely close down. It is likely that also these processes will depend on the degree to which local industries are skill-related to other industries in the region. Analyses should therefore be expanded to include the growth and decline of existing industries and the time horizon needs to be extended. We believe that such a research agenda would go a long way in creating a more thorough understanding of the processes of structural change in local economies.

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Appendix A: Multinomial logit regression

Table 4: Multinomial regression analysis of expansion events by agent

	entrepreneurs			firms		
	local	regional	outside	local	regional	outside
skill-proximity to PF	0.0609*** (75.55)	0.0772*** (81.44)	0.0763*** (86.20)	0.0526*** (33.25)	0.0592*** (27.11)	0.0682*** (51.04)
ln(employment municipality)	0.5250*** (69.65)	0.4565*** (46.41)	0.6662*** (71.77)	1.2400*** (67.79)	1.1261*** (46.78)	1.1466*** (80.07)
ln(employment industry)	0.4216*** (63.60)	0.5096*** (58.87)	0.6867*** (81.83)	1.5742*** (89.44)	1.0917*** (46.79)	0.8825*** (61.43)
constant	-12.10*** (-121.07)	-13.13*** (-99.59)	-16.71*** (-128.13)	-32.40*** (-109.24)	-27.14*** (-72.34)	-24.39*** (-108.49)
# observations	362790					

t-statistics in parentheses. * $p < 0.025$, ** $p < 0.01$, *** $p < 0.001$. All expansion events have been classified into one of six mutually exclusive groups corresponding to the agent that set up the new plant. If one local industry experienced expansion events by multiple agents, we classified the event as caused by the class of agents that as a whole sets up the lowest amount of plants. That is, the order of preference is: regional firms, local firms, outside firms, outside entrepreneurs, regional entrepreneurs, and local entrepreneurs.

Table 1: Top 10 skill-related industries

Industry 1	Industry 2	Skill-relatedness
5510: Hotels	5530: Restaurants	73.4
5530: Restaurants	5510: Hotels	66.3
5010: Sale of motor vehicles	5020: Maintenance and repair of motor vehicles	43.3
6340: Activities of other transport agencies	6024: Freight transport by road	23.9
4533: Plumbing	4531: Installation of electrical wiring and fittings	22.9
2212: Publishing of newspapers	7440: Advertising	22.0
6411: National post activities	6340: Activities of other transport agencies	21.8
6024: Freight transport by road	6340: Activities of other transport agencies	21.1
7222: Other software consultancy and supply	7414: Business and management consultancy activities	19.9

The table only includes industries that had on average over 10,000 employees a year in the period 2004-2007.

Table 2: New plants and new plant employment over the period 2004-2007

	employment	# new plants	plant size
local entrepreneurs	180,292	104,275	1.7
regional entrepreneurs	62,825	37,108	1.7
entrepreneurs from outside the region	46,993	24,720	1.9
TOTAL	290,110	166,103	1.7
local firms	56,701	5,587	10.1
regional firms	19,489	1,669	11.7
firms from outside the region	41,829	5,717	7.3
TOTAL	118,019	12,973	9.10

Note: employment refers to the employment in the first year of a new plant's existence.

Table 3: Logit regressions for expansion events in a local industry

	(1)	(2)	(3)	(4)
skill-proximity to PF	0.1132*** (215.44)		0.1142*** (210.51)	0.0657*** (104.08)
classification proximity to PF		0.0337*** (60.48)	-0.0049*** (-7.40)	0.0035*** (4.73)
ln(employment municipality)				0.6177*** (110.10)
ln(employment industry)				0.5946*** (121.97)
constant	-3.482*** (-328.84)	-2.089*** (-263.66)	-3.445*** (-294.68)	-13.78*** (-185.88)
# observations	362790	362790	362790	362790

t statistics in parentheses. * p<0.025, ** p<0.01, *** p<0.001

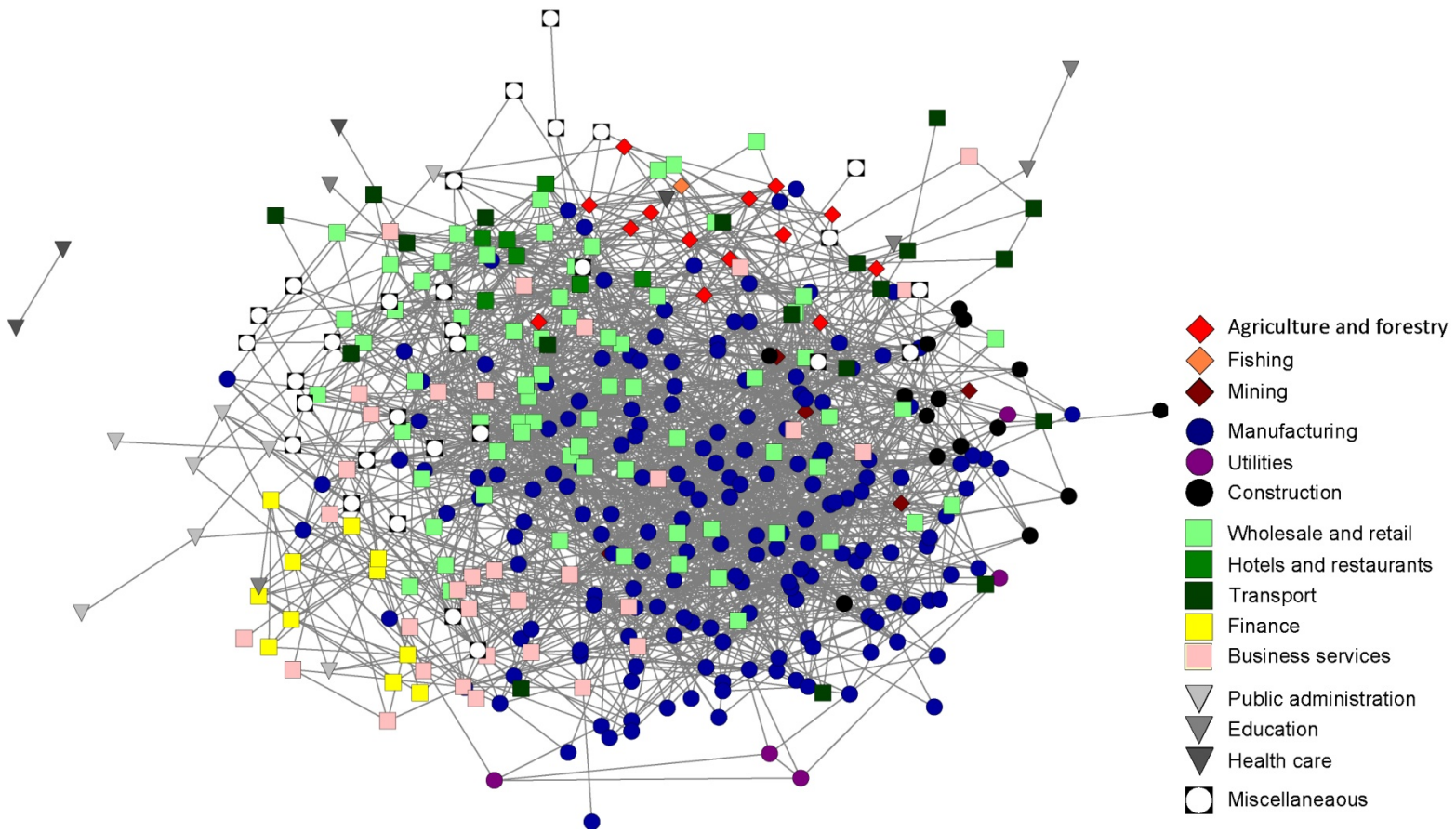


Figure 1: industry network in Sweden using skill-relatedness.

Note: only strongest 2500 links have been depicted

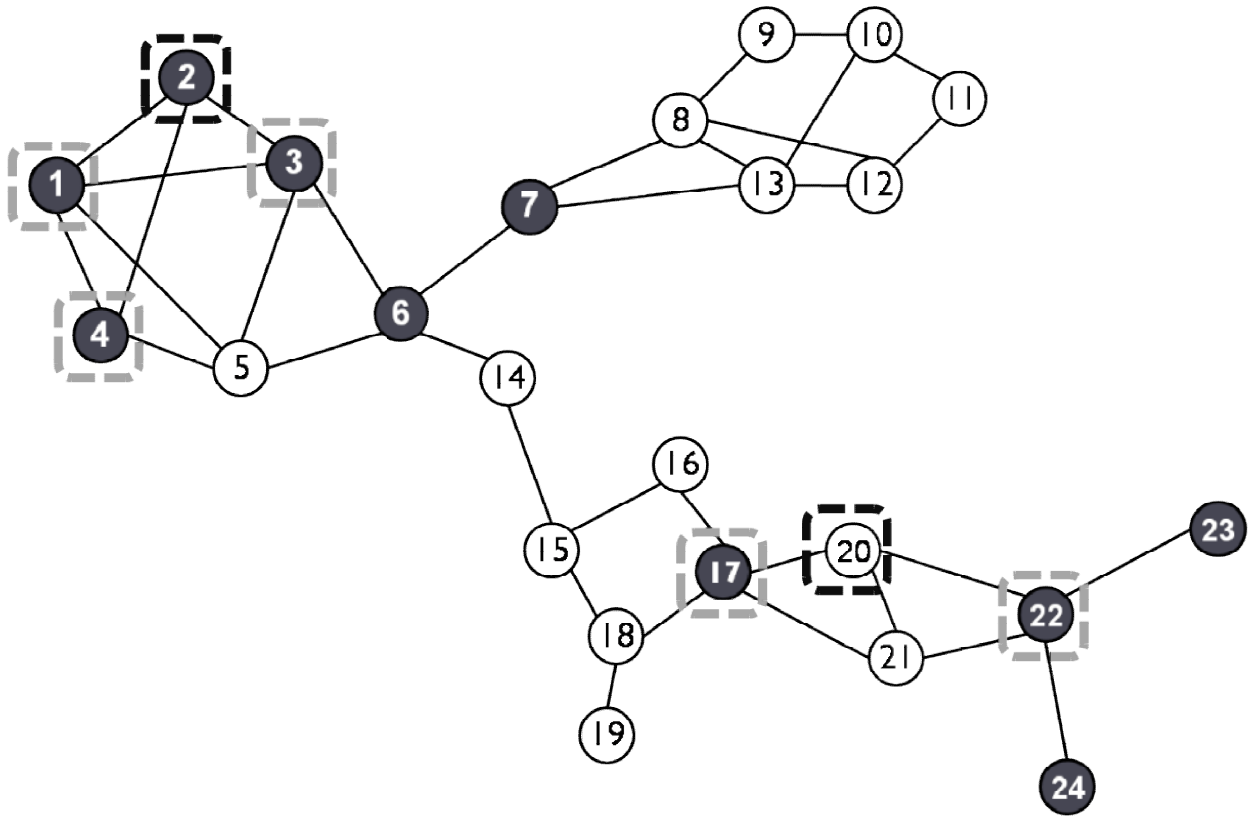
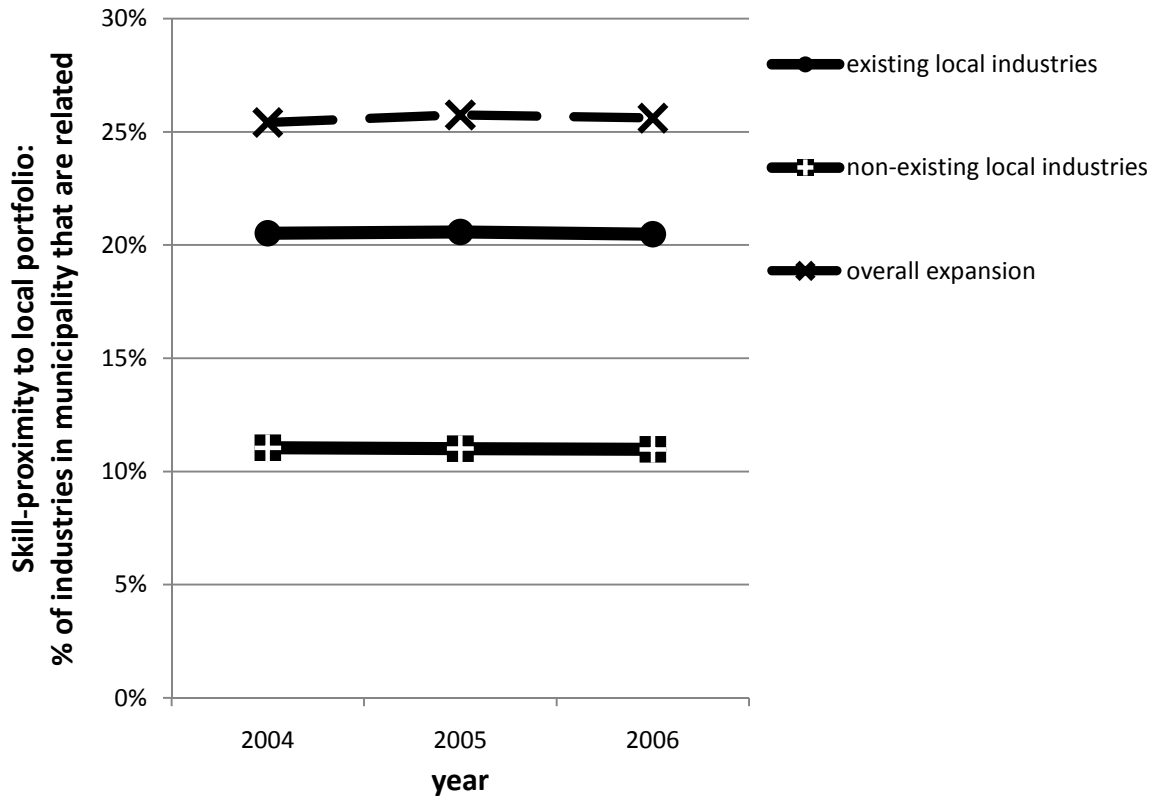


Figure 2: Simplified skill-relatedness industry space with municipality m 's portfolio in the dark circles. Skill-proximity of the existing industry 2 to the local portfolio equals 3, the non-existing local industry 20 has a closeness value of 2.

A: Regional expansion



B: Regional expansion by agent

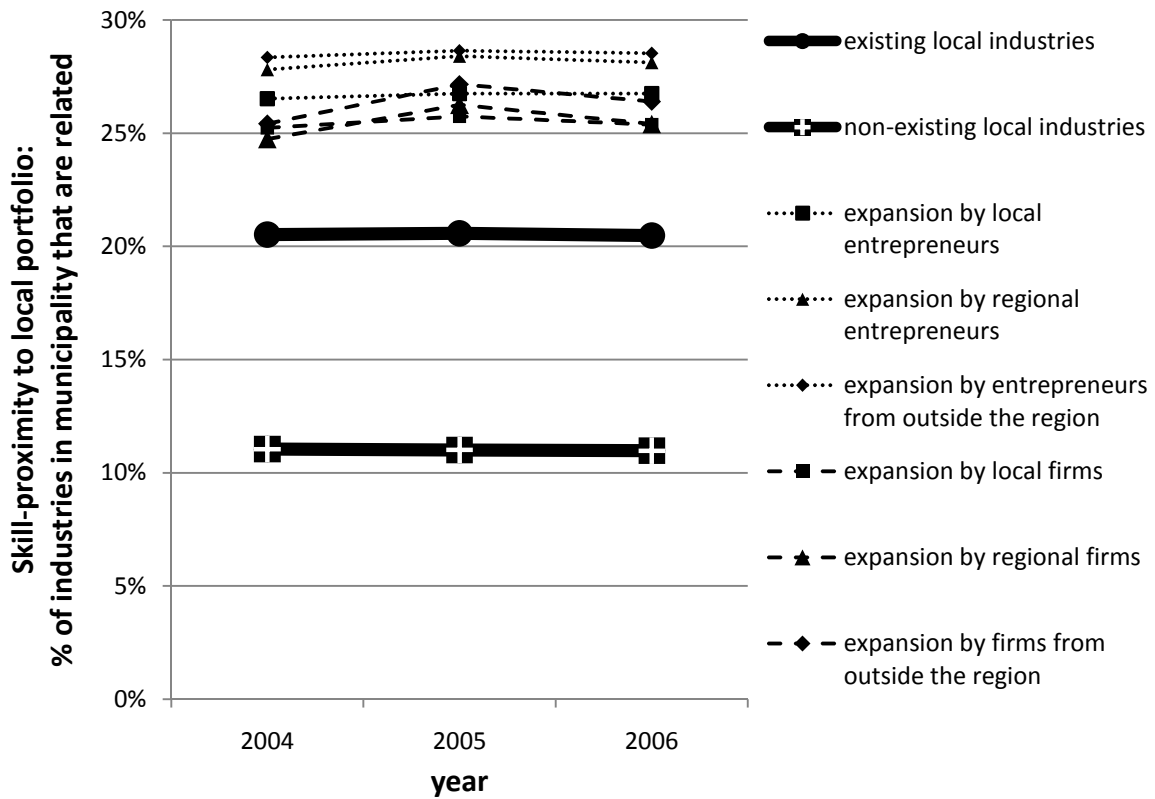
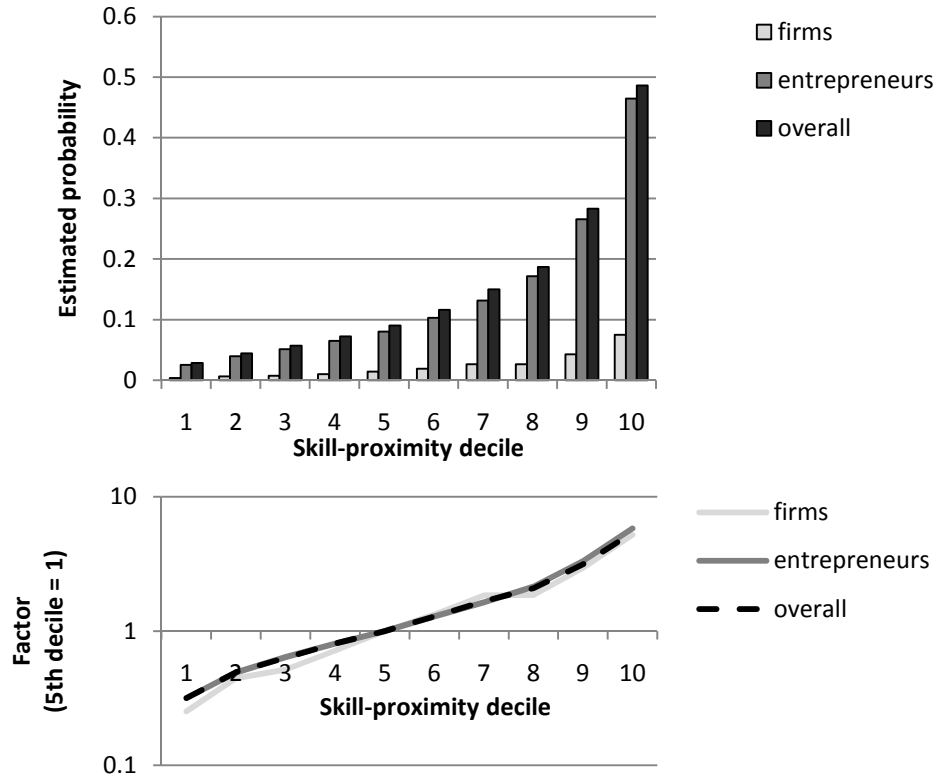


Figure 3: Average skill-proximities of local industries involved in expansion events

A: Regional expansion



B: Regional expansion: Entrepreneurs

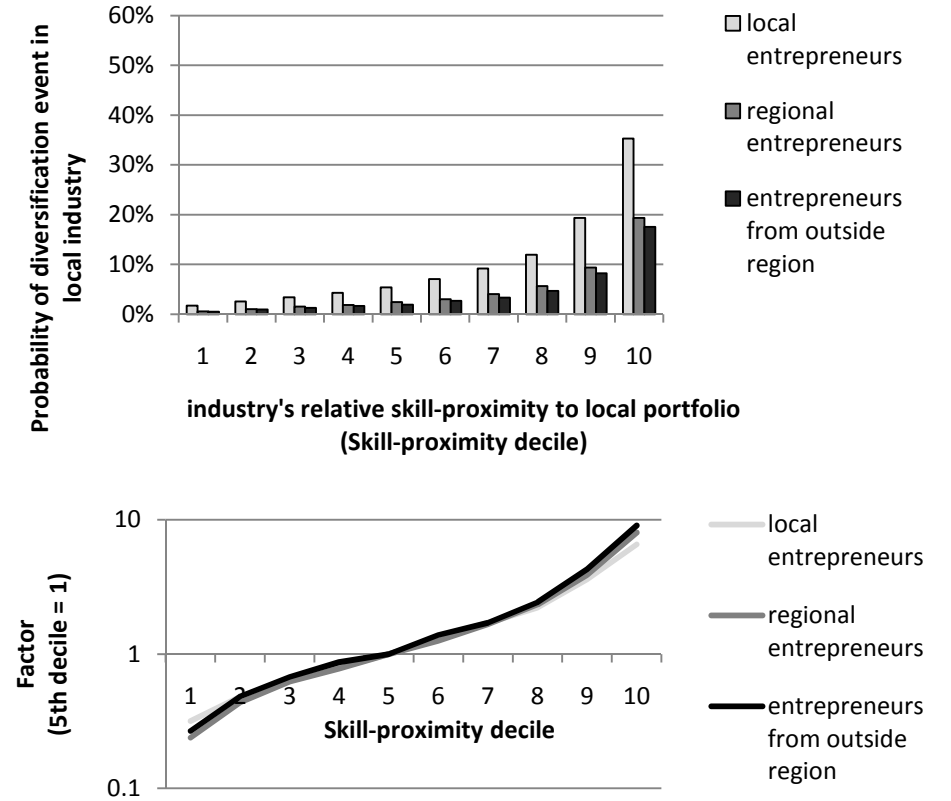


Figure 4: Probability of expansion events by skill-proximity decile

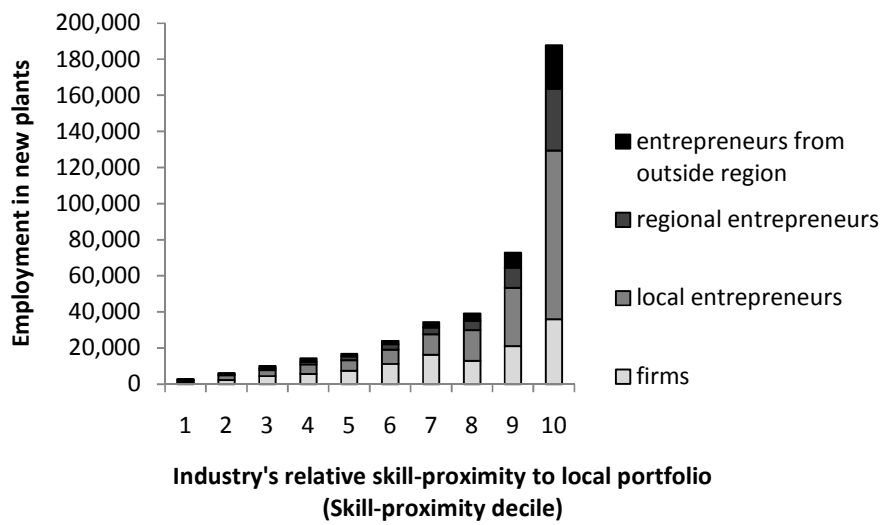


Figure 5: New plant employment by skill-proximity decile