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# How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions

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## abstract

The question of how new regional growth paths emerge has been raised by many leading economic geographers. From an evolutionary perspective, there are strong reasons to believe that regions are most likely to branch into industries that are technologically related to the preexisting industries in the regions. Using a new indicator of technological relatedness between manufacturing industries, we analyzed the economic evolution of 70 Swedish regions from 1969 to 2002 with detailed plant-level data. Our analyses show that the long-term evolution of the economic landscape in Sweden is subject to strong path dependencies. Industries that were technologically related to the preexisting industries in a region had a higher probability of entering that region than did industries that were technologically unrelated to the region's preexisting industries. These industries had a higher probability of exiting that region. Moreover, the industrial profiles of Swedish regions showed a high degree of technological cohesion. Despite substantial structural change, this cohesion was persistent over time. Our methodology also proved useful when we focused on the economic evolution of one particular region. Our analysis indicates that the Linköping region increased its industrial cohesion over 30 years because of the entry of industries that were closely related to its regional portfolio and the exit of industries that were technologically peripheral. In summary, we found systematic evidence that the rise and fall of industries is strongly conditioned by industrial relatedness at the regional level.

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Understanding regional development requires one to think about qualitative change, not quantitative change. Although quantities like regional growth in employment or in gross product may summarize changes in the fortunes of a region, these changes are themselves often the outcome of changes in the mix of economic activities in the region. Regions are subject to a never-ending process of creative destruction that Schumpeter (1939) identified as the driving force behind economic development. In the long run, regions depend on their ability to create and attract new industries to offset the decline in and destruction of other parts of their economies. This view inspired economic geographers in the 1980s to investigate the geographic implications of creative destruction (e.g., Norton and Rees 1979; Marshall 1987; Hall and Preston 1988). Since then, many detailed case studies have investigated both the successes of new growth regions, such as Silicon Valley in the United States and Bavaria in Germany, and the failures of many old industrial regions to restructure their economies (see, e.g., Scott 1988; Grabher 1993).

However, as yet there has been no systematic study of how regions diversify over time, how new growth paths in regions develop, and how old industrial regions revive their local economies (Martin and Sunley 2006). This absence of large-scale statistical research is not surprising, given that the process of structural change is highly idiosyncratic and involves different industries in different regions. The qualitative nature of the phenomenon makes it difficult to compare the process of structural change in one region to one that occurred in another region in more quantitative terms. In this article, we present a new framework, based on the concept of technological relatedness, that renders the phenomenon of structural change amenable to quantitative analysis. The contribution of this article is threefold. First, by building on an evolutionary economic framework, we provide theoretical justification for why regions do not achieve structural change simply by diversifying into any new industry but, rather, branch out into technologically related industries. In particular, we argue that technological relatedness gives rise to pronounced path dependencies in the diversification processes of regional economies.

Second, we empirically validate the hypothesis that regional structural change follows a branching process by using a novel indicator of interindustry relatedness. On the basis of this indicator, we can

depict the economy as a network of industries that are linked by their degree of technological relatedness, which we refer to as *industry space*. Furthermore, the indicator allows us to quantify the amount of structural change that the entry or exit of an industry represents to a particular region. This quantification takes into account that the entry of new advanced financial services in Malmö (traditionally one of Sweden's manufacturing cities), for instance, represents a higher degree of structural change than the entry of this industry in Stockholm (Sweden's main financial services center). Using data on 174 different manufacturing industries in 70 labor market regions in Sweden, we investigated the processes of regional creative destruction over a period of more than 30 years. By systematically studying which industries enter and which industries leave a region, we found that regions diversify because of the entry of industries that are technologically related to the existing industries in the region and that regions refocus their economies by the withdrawal of industries that are technologically unrelated to other local industries. Although we witnessed substantial structural change in the economies of Sweden's regions over time, the net effect of the entry and exit of local industries turned out to be that these regions, on average, maintained a more or less constant level of technological cohesion among their industries.

Third, in this article, we show that our quantitative framework can be regarded as complementary to qualitative approaches. An important challenge for many case studies of structural change is to keep track of the overall consequences of events in individual industries. That overview is easily lost, for instance, because a decline in one industry typically affects the embeddedness of all other industries in the region. In a highly stylized case study of the Linköping region, we showcase how the concept of industry space can facilitate the case-study analysis of structural transformation. We use this example to illustrate how the industrial cohesion of a regional economy and its subsequent structural change can be represented graphically. In addition, we show how the successive exits of related industries in Linköping seem to have initiated a cascading sequence of further exits that ended with the loss of an entire technological cluster of industries in the region. The analytical tools we developed can identify the parts of the economy that are likely to play an important role in the restructuring of a region, thus helping to delimit the scope of an in-depth case study of the region.

In the second section, we discuss the relationship between industry relatedness and structural change in an evolutionary framework. We discuss how the industrial relatedness measure is created in the third section. In the fourth section, we describe our data set. In the fifth section, we empirically study processes of regional structural change by analyzing the industrial portfolios in Sweden's regions. The sixth section discusses the role of relatedness in the Schumpeterian process of creative destruction at the regional level. The seventh section presents the case study of the Linköping region, and the final section presents our conclusions and establishes an agenda for future research.

## Relatedness and the Economic Evolution of Regions

In the field of economic geography, there has been a sustained interest in the question of how countries and regions develop over time. In the 1990s, a rapidly expanding literature focused on whether countries and regions converge or diverge over time (see, e.g., Barro and Sala-i-Martin 1995). At about the same time, the New Economic Geography focused on how globalization and economic integration affect spatial clustering (Krugman 1991). However, both approaches failed to incorporate tendencies toward structural change into their respective theories and neglected the geographic dimension of

creative destruction according to which the catching up and falling behind of countries and regions should be analyzed in terms of the rise and fall of industries (Dosi 1984; Hohenberg and Lees 1995).

In contrast to these relatively new strands of literature, economic geographers had already embraced Schumpeterian ideas. In the 1980s, these scholars used spatial versions of the industry life cycle to explain the long-term dynamics of the economic landscape (e.g., Norton 1979; Markusen 1985). They observed that regions that were developing new industries overtook regions that were locked into more mature industries. A classic example is the rise of the Sun Belt states in the United States, which left behind the Snow Belt states, which were heavily specialized in old and declining industries. One of the claims of this literature was that old industrial regions, with their labor unions, high wages, and crowded streets, had fallen victim to their own past industrial success (Storper and Walker 1989). In contrast, new growth regions did not suffer from such a legacy and were depicted as if they could start from scratch when developing new growth industries. However, this literature did not pay much attention to whether existing regional industrial structures might boost the emergence and growth of new industries. Nor did it thoroughly

240

address the possible rebirth or revival of old industrial regions. At about the same time that Krugman (1991) published his seminal work, urban economists stumbled upon the question of structural change through a reappraisal of the works of Jane Jacobs (1969). Glaeser, Kallal, Scheinkman, and Schleifer (1992) extended the agglomeration externalities framework, which, until then, had dealt primarily with the effects of localization economies and urban size by investigating the economic importance of urban diversity. This focus on so-called Jacobs externalities can be regarded as a first rough attempt to assess the effect of the local industrial structure. Henderson, Kuncoro, and Turner (1995) took a further step in the direction of investigating structural change by studying whether the types of externalities that were important for sustaining mature industries were different from the ones that mattered for attracting new industries. They found that new (high-tech) industries entered diversified cities where Jacobs externalities were available, whereas mature industries benefited more from the localization externalities that were generated in more specialized cities. Duranton and Puga (2001), in their nursery cities concept, formalized the idea that the agglomeration benefits that firms draw from their local environment depend on the firms' maturity. Neffke et al. (2011) provided further empirical evidence of the hypothesized link between agglomeration externalities and the life cycle stage of an industry.

Jacobs's (1969) original explanation of why new industries require diversified urban economies was that urban diversity facilitates a deep division of labor in a city. However, this division of labor contributes to urban growth not so much for efficiency reasons, as Adam Smith once argued, but because it gives rise to opportunities for innovation. This idea fits nicely within the Schumpeterian framework, which regards innovation as successful new combinations of old ideas. A more important but long-neglected implication of Jacobs's observation is that it abandons the image of knowledge as an amorphous *quantity* in favor of knowledge as an interconnected set of qualitatively different ideas. In cognitive theory, such a depiction has led to an emphasis on the trade-off between diversity and similarity: although actors who share a greater overlap in competences may find it easier to communicate with one another, only actors that dispose of nonoverlapping competences and knowledge can actually offer something new to be learned. As a matter of fact, a too-strong overlap in competences may even lead to cognitive lock-in (Nooteboom 2000).

The notion that an *optimal* level of cognitive distance may exist in social learning may explain why, after many empirical studies, evidence of the effects of Jacobs externalities

is at best inconclusive (e.g., De Groot, Poot, and Smith 2009). Regional knowledge spillovers will not take place between just any industries because effective communication is often hampered by excessive cognitive distance. Hence, scholars have recently suggested that industries are more likely to learn from one another when they are technologically related.<sup>1</sup> Accordingly, a range of technologically related industries in a region should be more beneficial than a diversified but unrelated set of industries because related industries combine cognitive distance with cognitive proximity, bringing together the positive aspects of variety across and relatedness among industries.

Along these lines, Frenken, Van Oort, and Verburg (2007) argued that regions with a higher degree of variety among related industries in a region will exhibit more learning opportunities and consequently more local knowledge spillovers. They showed that regions with a high degree of related variety were indeed associated with the highest growth in employment in the Dutch economy, a finding that was later replicated in other countries (Essletzbichler 2007; Bishop and Gripaio 2010). Boschma and Iammarino (2009) argued that new and related variety may also flow into a region through interindustry trade linkages with other regions. Making use of data on regional trade, they found that inflows of extraregional knowledge indeed correlated with a growth in regional employment when these flows originated from industries that were related, but not identical, to the industries in the region.

In these studies, the industrial base of a region was treated as a stable property. This treatment makes sense in the short run because the industrial composition of a regional economy changes only slowly from one year to the next. However, it is likely that relatedness among regional industries not only drives the incremental growth of existing industries through agglomeration externalities but may also be responsible for more dramatic shifts in the regional production structure. Indeed, we argue that the relatedness of industries may be an important factor in the attraction of new industries to and the disappearance of old ones from a region. As a consequence, relatedness is a fundamental concept because it is likely to shed light on how the Schumpeterian process of creative destruction unfolds at the regional level in the long run. The question of how new regional growth paths emerge has repeatedly been raised by leading economic geographers in the past (Scott 1988; Storper and Walker 1989) and present (Martin and Sunley 2006, 2010; Simmie and Carpenter 2007) as one of the most intriguing and challenging issues in the field of economic geography. We expect that the industrial history of regions, particularly the parts of the technology space that their portfolios inhabit, will affect the ways in which regions create new variety over time and how they transform and restructure their economies.<sup>2</sup>

Case studies have described many examples of new local industries being deeply rooted in related activities in a region (see, e.g., Bathelt and Boggs 2003; Glaeser 2005; Klepper 2007). Boschma and Wenting (2007) showed that in the early development stage of the UK automobile industry, firms had a higher survival rate when their entrepreneurs had previously worked in related industries, like bicycle making, coach making, or

<sup>1</sup> In the 1990s, similar ideas were developed around the notion of technology systems (Carlsson and Stankiewicz 1991).

<sup>2</sup> This is not to deny that there are other ways to diversify regional economies than through related diversification. For instance, new industries may enter a region as a result of foreign direct investments in unrelated industries. In this article, however, we concentrate on how relatedness and related variety affect the process of regional diversification.



mechanical engineering, and when their regions featured a strong presence of these related industries. More systematic evidence is being presented that territories are more likely to expand and diversify into industries that are closely related to their existing activities (Hausmann and Klinger 2007; Hidalgo, Klinger, Barabási, and Hausmann 2007; Neffke 2009). Focusing on shifts in export portfolios over time, Hausmann and Klinger (2007) showed that countries predominantly expanded their export mix by moving into products that were related to their current export basket, implying that a country's position in the product space affected its opportunities for diversification. As a consequence, rich countries, which specialize in more densely connected parts of the product space, have more opportunities to sustain economic growth than do poor countries. This process by which new variety (industries) arises from technologically related industries in regions has been termed "regional branching" (Frenken and Boschma 2007; Boschma and Frenken forthcoming).

242 The implications of regional branching are not to be underestimated. First, the way in which the Schumpeterian process of creative destruction shapes the economic landscape at the regional level should be affected by industry relatedness because the relatedness among industries plays a role in determining which new industries enter and existing industries leave a region. Second, the rise and fall of industries are conditioned by regional industrial structures that have been laid down in the past, which would support the notion of regional path dependence, according to which each region follows its own industrial trajectory (Rigby and Essletzbichler 1997). Third, this path-dependent process implies that there is some degree of cohesion in the industrial profile of a region. However, this cohesion is constantly being redefined through the process of creative destruction. The entry of new industries into a region, although these industries are often technologically related to existing local industries, is likely to inject new variety into the region and will lower technological cohesion. In contrast, the exit of existing industries will increase the industrial cohesion of regions because unrelated industries are more likely to be selected out, leading to a decrease in variety. We empirically test these ideas to determine whether and to what extent regional industrial structures can be said to be cohesive and how this cohesion evolves through the creation of new industries and the destruction of existing local industries in a region. To quantify the changing cohesion among industries in a region, we need to determine the degree to which industries are related. Therefore, we now turn to measuring interindustry relatedness.

## Measuring Relatedness: The Revealed Relatedness Method

In empirical work, interindustry technological relatedness is often derived from the hierarchical structure of the standard industrial classification (SIC) system. The closer together industries are within this classification system, the more related they are thought to be. However, whether SIC-based relatedness measures are truly measures of *technological* relatedness can be questioned. As a response to the perceived shortcomings of SIC-based relatedness, measures of industry relatedness have, for instance, been based on similarities in upward and downward linkages in input-output tables (Fan and Lang 2000) or on similarities in the mixes of occupations that have been employed by different industries (Farjoun 1994). More recently, a number of scholars have turned to co-occurrence analysis to assess inter-industry relatedness (Teece et al. 1994; Hidalgo et al. 2007; Bryce and Winter 2009). Co-occurrence analysis measures the relatedness between two industries by assessing whether two industries are often found together in one and the same economic entity. Hidalgo et al. (2007) counted the number of times that two industries showed a revealed comparative advantage (the co-occurrence) in the same

country (the economic entity).<sup>3</sup> Similarly, Teece, Rumelt, Dosi, and Winter (1994) and Bryce and Winter (2009) counted the number of times one firm (the economic entity) owned plants in two different industries (the co-occurrence). However, other factors besides relatedness may partly determine the number of co-occurrences. For example, if industries are very large, they are likely to be found in many firms, and, therefore, they will also more frequently co-occur with other industries. To determine whether the number of co-occurrences between two industries is in some way excessive, co-occurrences are compared to a (“expected”) baseline. The more often two industries co-occur relative to this baseline, the higher their relatedness score.

In this article, we use a co-occurrence-based measure, called *revealed relatedness* (RR), which was developed by Neffke and Svensson Henning (2008) to estimate relatedness. Industry relatedness here is derived from the co-occurrence of products that belong to different industries in the portfolios of manufacturing plants. In essence, the RR index measures the revealed existence of economies of scope between industries. Note, though, that the RR version that we use in this article is derived from the product portfolios of *plants*, not from portfolios of firms, as in Teece et al. (1994) and Bryce and Winter (2009). The difference between the firm and plant levels is crucial because the set of economies of scope that matter at the plant level is more restricted than the set of economies of scope that matter at the firm level. If products from two industries are often found to be produced in one and the same plant, this is likely to happen because the production processes in these industries generate economies of scope for one another. For instance, the same machinery may be used in both industries, or both industries may require employees with similar skills. In other words, such industries are related to one another in a technological sense. In contrast, if technological economies of scope between two industries are absent, it is unlikely that firms will combine the corresponding different production processes in one plant, although it is still possible that one firm owns plants in both industries. For example, consider the sportswear manufacturer, Nike. Nike used its strong brand in the world of sports to diversify from its sports clothing line into sports watches. Consequently, at the firm level, both industries are found in one and the same portfolio. Nonetheless, without doubt, watchmaking and the manufacturing of sports apparel are unrelated in a technological sense. It is, however, also unlikely that Nike’s shirts and watches are produced in the same plants. Such economies of scope that exist only at the firm level, and not at the plant-level, do not affect the RR index, which will thus predominantly reflect the degree of *technological* relatedness among industries.

The construction of the RR index involves two steps.<sup>4</sup> In the first step, the number of co-occurrences between the industries is determined for each combination of two industries ( $i, j$ ). Let us denote the number of co-occurrences by  $L_{ij}$ . But the number of co-occurrences does not depend only on the relatedness among industries. For instance, firms are more likely to add highly profitable industries to their portfolios than industries with low profitability. Regardless of their relatedness to other industries, the probability of encountering a large industry in a co-occurrence is larger than the probability of encountering a small industry.

<sup>3</sup> Hidalgo et al. assessed relatedness among product categories. Product categories, however, can be translated fairly easily into industrial categories.

<sup>4</sup> In fact, there are three steps in Neffke and Svensson Henning’s (2008) approach. The final step uses Bayesian inference to increase precision when the information on co-occurrences is patchy because the industries involved are very small. The vast majority of estimates are unaffected by this step, and details can be found in Neffke and Svensson Henning (2008).



In the second step of the RR method, Neffke and Svensson Henning (2008) controlled for such effects by determining the number of co-occurrences for a combination  $(i,j)$  that would be *expected* on the basis of such industry-level characteristics alone. We therefore ran a regression of the observed co-occurrences  $L_{ij}$  on the overall profitability, employment, and number of active plants in both industries.<sup>5</sup> Using the estimated parameters, it is possible to calculate predictions of the number of co-occurrences,  $\hat{L}_{ij}$ , for each combination of industries  $(i,j)$ . For instance, in our data, the predicted “baseline” numbers of co-occurrences between industries were 382,200 (manufacture of agricultural machinery and equipment) and 384,320 (manufacture of motor vehicles engines, parts, and trailers) in 1980 based on profitability, the number of employees, and the number of plants in both industries, was 4.99. This prediction is then compared to the observed number of co-occurrences, which, for the foregoing example, was 36. This observed number of co-occurrences exceeds expectations by a factor of 7.21, which indicates that the industries are strongly related to one another. In the third step, this factor is multiplied by a constant to arrive at an index that lies between 0 and 1 for all industry combinations.<sup>6</sup> The basic estimate of RR can be written as follows:

244

$$RR_{ij} = k \frac{L_{ij}}{\hat{L}_{ij}}, \quad (1)$$

where  $k$  is the normalizing constant. For 1980, this constant equals  $\frac{1}{11.97}$ . Consequently, the relatedness between the agricultural machinery industry and the motor vehicles industry is 0.59.<sup>7</sup>

It is important to note that the RR index is an estimate and is likely to exhibit some degree of measurement error. We do not think, however, that the RR index is particularly susceptible to measurement error in comparison to other indexes, but the use of even larger databases could further improve the estimates. Furthermore, alternative measures may be used to capture other interindustry linkages besides technological linkages, such as labor market or input-output linkages. The remainder of this article uses the RR index because we think that structural change is primarily a technological phenomenon. If other relatedness indexes are available, it is, however, easy to substitute them for the RR index in the analyses that follow. Doing so may lead to the discovery of interesting complementarities among different types of relatedness, but this is beyond the scope of this article.

## The Swedish Spatial System and Data

Having quantified which industries are related, we are now in a position to examine the role that relatedness plays in regional structural change. The population of Sweden

<sup>5</sup> Neffke and Svensson Henning (2008) also included the total sales value and the value added of an industry. However, the explanatory force of these variables strongly overlaps with that of the industry's profitability, so we decided to drop these variables. Our relatedness measure is therefore slightly different from the original one, but with a rank correlation between both measures of 0.90 they are very similar.

<sup>6</sup> The normalizing procedure does not substantially change the index but only redefines the units in which it is measured. Neffke and Svensson Henning normalized the index because relatedness values must be restricted to the interval of  $[0,1]$  to enhance the quality of relatedness estimates using indirect information. Details can be found in Neffke and Svensson Henning (2008).

<sup>7</sup> The distribution of RR values is skewed. Many combinations of two industries, approximately 25 percent, are unrelated, and most industry combinations therefore have an RR index of 0. Furthermore, almost 90 percent of all industry combinations are marginally related, with an RR index of less than 0.1. RR values in excess of 0.25 account for some 5 percent of all industry combinations.

increased from about 8.1 million in 1970 to 8.9 million in 2000. It is, however, unequally distributed over space, since all but a small minority of inhabitants live in the middle or southern parts of the country, leaving the northern parts with vast and scarcely populated areas. In terms of regions, we used the 70 Swedish functional A-regions that are often used for long-term analyses. Typically, these regions consist of a number of smaller municipalities around a major urban center.

We used two data sets that were originally obtained from Statistics Sweden. The data set that we used to estimate industry relatedness contains information about the products that were produced in Swedish manufacturing plants from 1969 to 2002. The product codes used in this data set were first translated into standard industry codes according to the SNI69 system, which was used in Sweden until it was replaced by its successor, the SNI92 system, in the 1990s. We used data-imputation methods to translate SNI92 codes into SNI69 codes if the latter were missing. The analyses for the entire period thus used the same classification system. We then used the industry codes to define the plants' portfolios. For example, if a plant produces two different products, say,  $a$  and  $b$ , and these products are classified as belonging to industries  $i$  and  $j$ , this counts as a co-occurrence between industries  $i$  and  $j$ . The data set is described in more detail in the appendix.

To determine which industries were active in each of the 70 Swedish regions at some point between 1969 to 2002, we used a second data set that contained information on plant-level employment and industry affiliation and aggregated these data to the regional level. The data set and sampling regimes are described in greater detail in the appendix. Unlike the data on product portfolios, each plant in this database has only one industry affiliation (which corresponds to its main activity). Therefore, the fact that two industries co-occur in one plant in the product portfolio database does not imply that both industries are also both found in the region where the plant is located. For two industries to be present in the same region, each needs to have at least one plant in the region the main activity of which belongs to the particular industry. Thus, plant-level co-occurrence does not automatically imply co-occurrence at the regional level.

## Relatedness and Structural Change in Regions

Using the product portfolio data sets, we estimated a matrix of RR indexes that covers 174 six-digit industries in the Swedish manufacturing sector.<sup>8</sup> Figure 1 illustrates this matrix by depicting *industry space*, a network graph that connects related industries. Each node in the graph represents a six-digit industry, and the different colors and symbols reflect the various two-digit SNI69 categories to which they belong. Lines that connect the industries represent RR linkages. The arrangement of industries in this graph is such that, in general, more related industries are located closer together in the two-dimensional plane.<sup>9</sup> Therefore, industry space can be used to get a first impression of which industries are relatively closely related to one another because more related industries also tend to cluster together in industry space.

<sup>8</sup> We calculated a RR matrix for each year from 1969 to 2002. In principle, RR can change, reflecting dynamics in the technological distances between industries. The general relatedness structure of the economy is, however, fairly stable, although some shifts are visible in these 30 years of economic development. Investigating the consequences of treating relatedness as a dynamic concept is, however, left for future research. In the analysis reported here, we used average relatedness indexes over time to arrive at a single RR matrix.

<sup>9</sup> We used the spring-embedded algorithm of the *NetDraw* software (Borgatti 2002). Only the 2,500 strongest links are displayed.

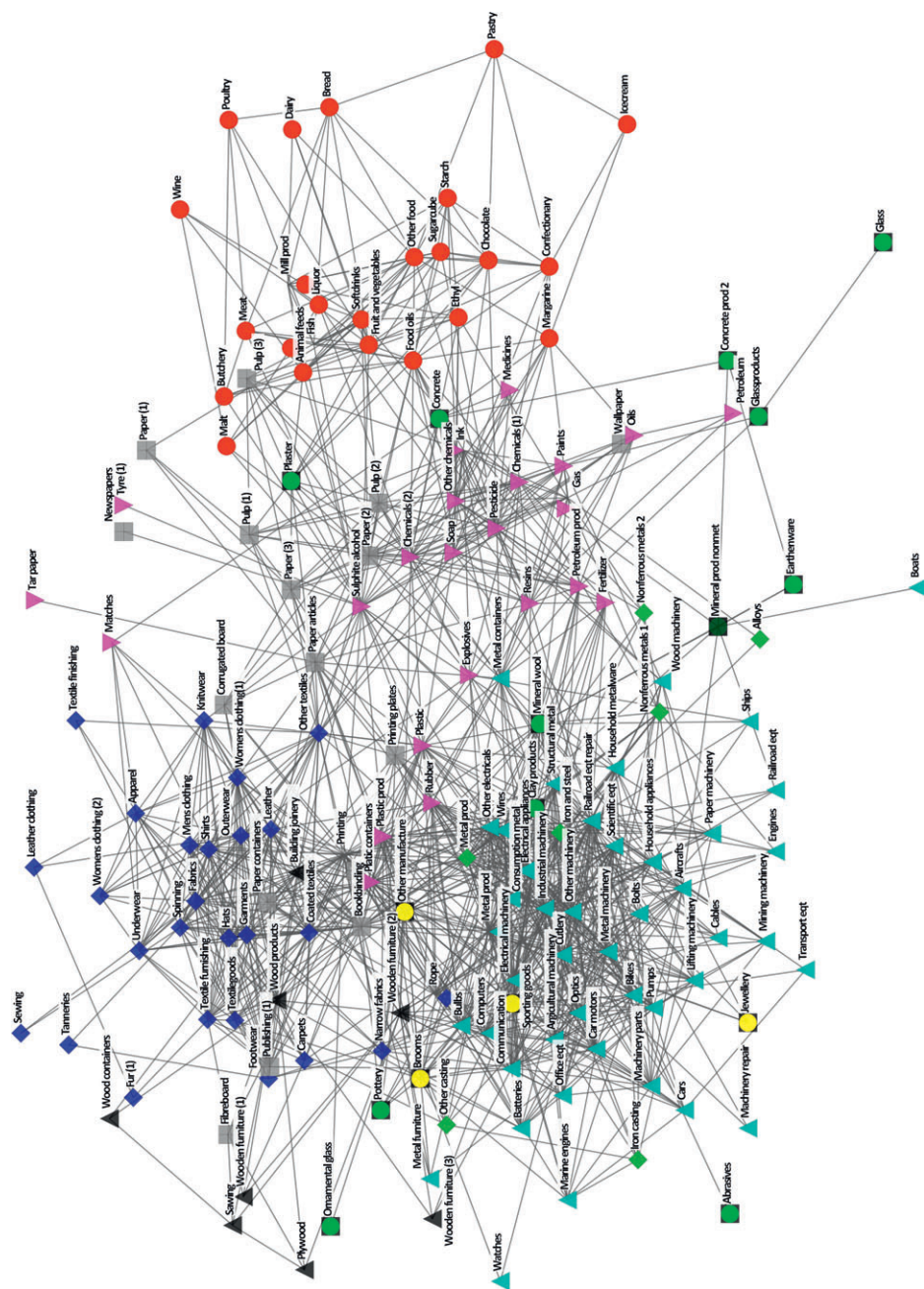


Figure 1. The average industry space in Swedish manufacturing, 1969–2002.

A striking feature of the graph depicted in Figure 1 is that industries form clearly distinguishable sets of related industries. We refer to these sets of industries that are close to one another in industry space as *technological clusters*. This term should not be confused with the term *geographical clusters*, which refers to the phenomenon of spatial clustering of industries. To some extent, technological clusters follow the hierarchical structure of the two-digit SNI codes. For example, machinery industries (light blue upward triangles), textiles industries (dark blue diamonds), and food industries (dark red circles) all cluster together in industry space. Yet there are also many exceptions: some steel and metal industries (light green diamonds) are located near the machinery cluster, and the concrete industry is located more closely to the chemicals cluster than to many of its fellow mineral products industries (dark green circles in black boxes). In fact, SNI relatedness, as defined by the proximity between two industries in the SNI69 hierarchy, has a 0.38 correlation<sup>10</sup> with our RR index. This moderate correlation shows that although industry space indeed corresponds to the SNI69 hierarchy to a certain degree, it by no means completely coincides with it. Moreover, unlike the SNI69 hierarchy, industry space also shows how different technological clusters of related industries are positioned relative to one another. For example, the textiles industries are more closely related to many machinery and metal industries than to most food industries. This finding confirms the intuition that spillover potentials between the machinery and textiles industries should be greater than those between the textiles and food industries.

Because our aim was to investigate whether the process of creative destruction is affected by industrial relatedness at the regional level, we first examined the magnitude of this regional structural change. Figure 2 shows the dynamics of Swedish local industries over the entire period under study. From 1969 to 2002, Swedish regions underwent substantial structural change. With regard to local industries (industry-region combinations that existed in the whole of Sweden in 1969), only 55.0 percent still existed in 2002. Taking the reverse perspective, 68.7 percent of all local industries in 2002 already existed in 1969.

In previous sections, we argued that such processes of structural change in regional economies are expected to follow a distinctly evolutionary logic of regional branching and path dependence. Accordingly, new economic activities are not developed in just any industry, but only in industries that are technologically related to the industries that are already present in a region.

The RR index measures how related one industry is to another industry. In other words, it quantifies the bilateral relationship between two industries. However, a regional portfolio typically consists of multiple industries. Therefore, to investigate how well an industry fits into the industrial structure of an entire region, we needed a measure that expresses the technological closeness of one industry to a set of industries, that is, to the regional portfolio of industries. We used an index that counts the number of industries in region  $r$ 's portfolio that are more closely related to industry  $i$  than a specific threshold value.<sup>11</sup> Region  $r$ 's portfolio,  $PF_r$ , is defined as all industries for which we observed nonzero employment in the region. Keeping in mind that all RR values lie between 0 and 1, we chose this threshold to be 0.25, but the results are similar for a wide range of

<sup>10</sup> This number represents the rank correlation between the off-diagonal elements of the RR matrix and the corresponding SNI relatedness.

<sup>11</sup> We also experimented with an index that calculates the distance of an industry to the technological envelope of a region. That is, we calculated the distance between the industry and the closest industry that was a member of the regional portfolio. The results we present are similar to the ones we get when using this alternative measure.

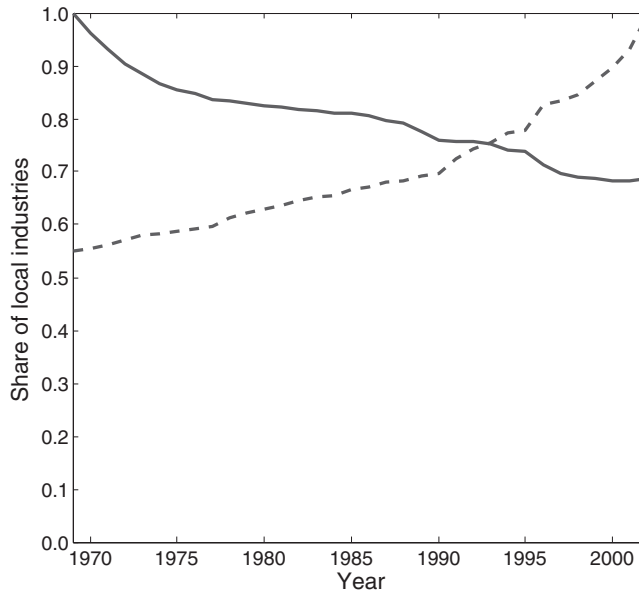


Figure 2. Structural change in Swedish regions, 1969–1994.

The solid line shows, for the whole of Sweden, the share of local industries that belonged to the original set of local industries in 1969 as a percentage of the total amount of local industries in each subsequent year. The dotted line shows its complement, namely, the share of local industries in each of the preceding years that would still exist in 2002.

threshold values.<sup>12</sup> If  $I(\cdot)$  is an indicator function that takes the value 1 if its argument is true and 0 if its argument is false,  $closeness_{ir}$  can be defined as

$$closeness_{ir} = \sum_{j \in PF(r)} I(RR_{ij} > 0.25). \quad (2)$$

Figure 3 illustrates this calculation. We plotted a regional portfolio in this graph by shading all local industries of the region. Lines that connect two nodes indicate that two industries are related, which means that the relatedness between them is at least 0.25. For instance, industry 3, which is part of the regional portfolio, is related to industries 1, 2, 5, and 6. Industries 1, 2, and 6 are part of the regional portfolio. Because, in total, three industries exhibit relatednesses of at least 0.25 to industry 3, the closeness of industry 3 to the regional portfolio is 3. Similarly, we can see that the closeness of industry 20, which is absent in this particular region, is equal to 2.

The average of the closeness values across all industries that are present in a regional portfolio can be regarded as a quantification of the *technological cohesion* of a regional economy:

$$technological\ cohesion_r = \frac{1}{N_r} \sum_{i \in PF} closeness_{ir}, \quad (3)$$

where  $N_r$  is the number of industries in the regional portfolio.

<sup>12</sup> In particular, we used thresholds of 0.02 and 0.58, which roughly correspond to classifying 25 percent and 1 percent, of all industry combinations, respectively, as strongly related. Using these values, we observed patterns that are similar to those we describe in the remainder of the article.



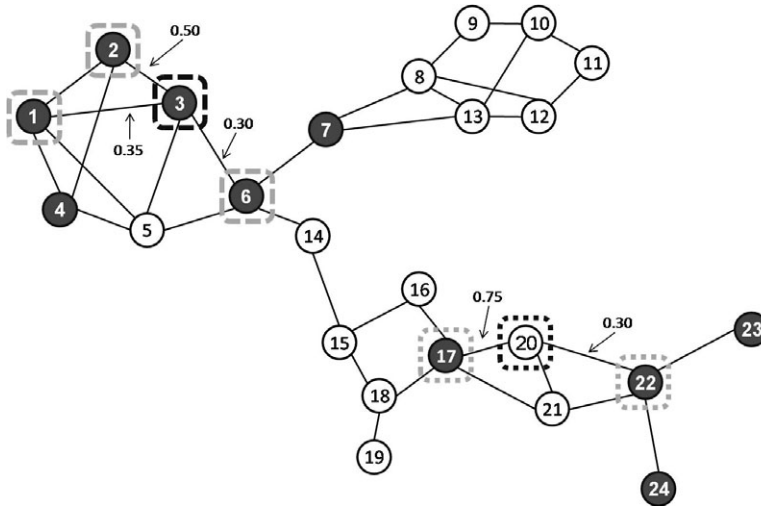


Figure 3. Illustration of closeness calculations.

The industries that belong to the regional portfolio are shaded. The numbers attached to the arrows indicate the relatedness between two industries. If there is a line connecting two nodes, the relatedness between them is greater than 0.25. We focus on industries 3 and 20. For industry 3, the closeness to the regional portfolio is equal to 3, whereas industry 20's closeness to the portfolio is equal to 2.

For instance, in Figure 3, the technological cohesion of the depicted region equals  $(3 + 3 + 3 + 2 + 2 + 1 + 0 + 2 + 1 + 1)/10 = 1.8$ .

Figure 4 describes the evolution of the average technological cohesion across all Swedish regions. The solid line in this figure depicts the closeness of industries to their regional portfolios, averaged across the whole of Sweden at a five-year interval. The dotted line depicts the average closeness of all industries in the portfolio to the industries that are *not* part of the regional portfolio. This provided us with a baseline against which we compared technological cohesion. A regional portfolio is said to be *cohesive* if its members are closer to one another than to industries that do not belong to the regional portfolio (i.e., regions are cohesive if the solid line lies above the dotted line). In Figure 4, this is clearly the case for all the years.

Although cohesion seems to be a stable phenomenon over time, the graphs may obscure a substantial amount of structural change as new industries enter and existing industries leave regions. Therefore, for all the industries that exited or entered a region within a five-year window, we plotted their average closeness to the corresponding regional portfolios.<sup>13</sup> The dashed line with the upward triangles denotes the closeness of entering industries to the portfolio. The dashed line with the downward triangles denotes the closeness of exiting industries to the portfolio. The line that represents entries is always above the (dotted) nonportfolio line, which means that the industries that enter a region are strikingly closer to the region's portfolio than are the industries that remain outside this portfolio. In other words, regions indeed diversify into industries that are related to their current portfolios of industries. It is remarkable that not only the line that represents entries, but also the line that represents exits lies above the dotted, nonportfolio line. This

<sup>13</sup> We experimented with 1-year and 10-year time windows and one time window that covered the entire period, 1969–2002. None of the patterns presented in this article was affected. The results are available from us on request.



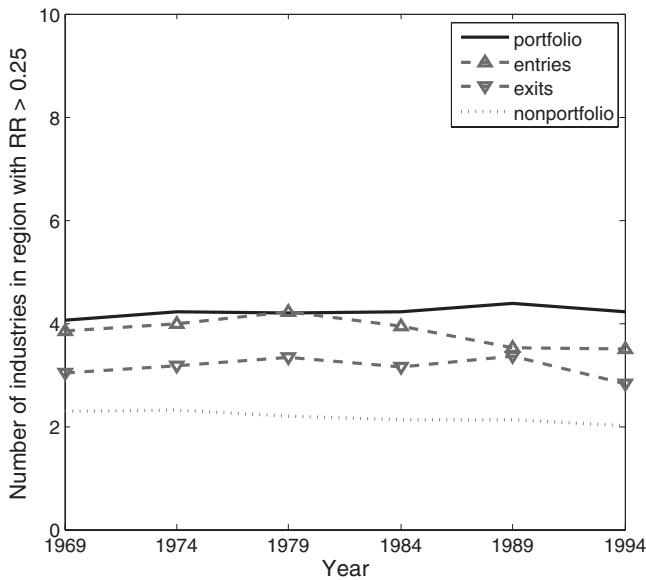


Figure 4. The evolution of Swedish regional production structures with closeness measures that specify the number of related industries with an RR higher than 0.25.

All lines depict averages across all regional industries in Sweden. Solid line: the closeness of portfolio members to the regional portfolio as a whole; dotted line: the closeness of absent industries to the regional portfolio; dashed line (upward triangles): the closeness of entering industries to the regional portfolio; dashed line (downward triangles): the closeness of exiting industries to the regional portfolio. All averages are significantly different from one another at least the 5% level, except for the entry and membership lines in 1974 ( $p$  value for test on equal averages = 0.09) and 1979 ( $p$  value = 0.62) and the entry and exit lines in 1989 ( $p$  value = 0.44).

finding is in fact not that surprising: we already showed that regional portfolios are generally cohesive, meaning that industries that were formerly members were probably not completely unrelated to the other economic activities in the region. However, the exit line is always well below the (solid) portfolio line. That is, although these exiting industries were not unrelated to the other local industries, on average, their technological position vis-à-vis the regional portfolio was rather peripheral.

A closer inspection of the entry line indicates that entries generally turn out to be less closely related to the portfolio than are existing portfolio members. If anything, the entry line is below the portfolio line, and entrants should decrease the technological cohesion of a portfolio.<sup>14</sup> This finding that entrants bring about novelty is in line with the evolutionary notion of mutations, according to which new activities increase variety in a population. Given that the exit line is well below the portfolio line, exits, on the other hand, should increase the average cohesion of a region, analogous to the variation-reducing effect of natural selection. The net effect of mutations and selection is a cohesion that seems to be remarkably stable over time.

<sup>14</sup> In practice, however, the entry of industries with a closeness to the portfolio members that is lower than the closeness among the portfolio members themselves can lead to a higher overall cohesion. This situation occurs whenever an industry fills a gap in the region's portfolio and takes a central position among a number of otherwise disparate portfolio members. Because of this bridging feature, these entries may have a huge effect on regional development, comparable to filling a structural hole in network theory.

In sum, we found three different regularities that are related to our research questions. The first is that regional production portfolios are cohesive and remain so over time. This finding indicates that if an industry is technologically close to a regional portfolio, the chances are high that it is actually a part of that portfolio. The second is that industries are more likely to enter a region if they are technologically related to the industries that were already present in that region. The third is that industries that belong to a portfolio but are at its technological periphery are more likely to leave the region. In the next section, we examine these results further.

## Portfolio Membership, Entry, and Exit

We start by defining dummy variables for membership, entry, and exit in the industrial portfolio of a region. The membership dummy variable takes on the value of 1 if an industry  $i$  is part of the industrial portfolio of region  $r$  at time  $t$ . The entry dummy variable takes on the value of 1 if an industry  $i$  does not belong to the industrial portfolio of region  $r$  at time  $t$  but has entered this portfolio by time  $t + 5$ . The exit dummy variable takes on the value of 1 if an industry  $i$  is part of the industrial portfolio of region  $r$  at time  $t$  but has left the region by time  $t + 5$ . Formally,

$$member_{irt} = I(i \in PF(r, t)) \quad (4)$$

$$entry_{irt} = I(i \notin PF(r, t) \wedge i \in PF(r, t + 5)) \quad (5)$$

$$exit_{irt} = I(i \in PF(r, t) \wedge i \notin PF(r, t + 5)) \quad (6)$$

Table 1 presents descriptive information about these dummy variables and about the overall size of regions and industries. Table 2 depicts the correlations between the dummy variables and the closeness to the regional portfolios if we pool data on all 70 regions and from all five-year periods between 1969 and 2002. For calculations involving the membership dummy variable, all the region-industry combinations are used as observations. However, industries that are already present in the region can obviously not enter the region, while for industries that are absent in the region, it is of course impossible to exit the region. Therefore, in calculations involving the entry dummy variable, we used the subsample of industries that were absent from the region at the beginning of a five-year period, and in those involving the exit dummy variable, we used the subsample of industries that were present in the region at that time. Adding both subsamples together results in the complete sample again.

As expected, entry and membership are both positively correlated with closeness, and exit is negatively correlated with closeness. Although these correlations may not strike one as particularly high, they are strongly significant in a statistical sense. To find out whether the impact of closeness on regional portfolios is also economically significant, we analyzed how these variables affect the probabilities of entry, exit, and membership. In the five-year samples, summed across all years and all periods, there were 2,766 events in which an industry entered a region. An industry could enter a certain region in a given period only if it did not yet belong to the region's portfolio at the beginning of the period. In total, there were 52,226 such entry opportunities. That is, summed across all periods, there were 52,226 industry-region combinations for which the industries did not belong to the portfolio of the corresponding region. As a result, we estimated the probability of entry to be  $2,766/52,226 = 5.3$  percent. Similarly, the overall probability of exit was

Table I

## Descriptive Statistics

	Number of Observations	Mean	SD	Minimum	Maximum	Correlation Matrix					
						(1)	(2)	(3)	(4)	(5)	(6)
(1) Member	72,100	0.289	0.453	0.00	1.00						
(2) Entry	51,246	0.053	0.224	0.00	1.00						
(3) Exit	20,854	0.166	0.372	0.00	1.00						
(4) Closeness (PF)	72,100	2.787	3.318	0.00	30.00	0.27	0.14	-0.11			
(5) Closeness (non-PF)	72,100	5.996	5.332	0.00	29.00	-0.07	0.03	0.02	0.31		
(6) Log[emp(r)]	72,100	8.947	0.850	6.19	11.60	0.25	0.06	-0.09	0.34	-0.21	
(7) Log[emp(i)]	72,100	7.625	1.381	2.20	10.82	0.36	0.14	-0.19	0.34	0.19	0.03

Note: Observations refer to industry-region combinations. The definitions of the variables are as follows: member: membership dummy variable; entry: entry dummy variable; exit: exit dummy variable; closeness (PF): the number of closely related industries that are present in the region, closeness (non-PF): the number of closely related industries that are absent from the region, log[emp(r)]: the logarithm of the sum of employment across all industries in the region, and log[emp(i)]: the logarithm of the sum of employment in the industry across all regions. The information on the entry and exit dummy variables was calculated using the restricted subsamples for which these dummy variables are defined.

Table 2

Correlations Between the Values for Closeness and the Membership, Entry, and Exit Dummy Variables

Dummy Variable	Correlation	p value	N
Member	0.278	<.001	73,080
Entry	0.142	<.001	52,226
Exit	−0.112	<.001	20,854

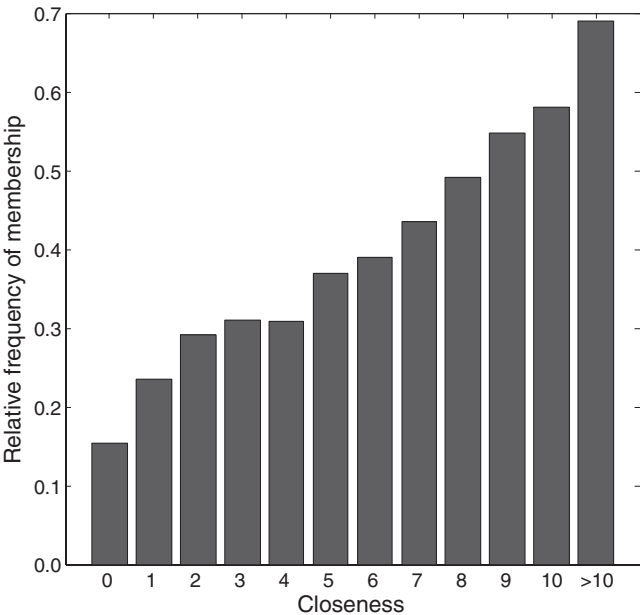


Figure 5. Probabilities of membership.

16.6 percent since there were 3,464 events of an industry leaving a region and 20,854 exit opportunities. Finally, we estimated the probability of membership to be 28.5 percent (out of a total of 73,080 possible regional industries, 20,854 are in existence). Each industry-region combination can be attributed to a specific closeness value using the method depicted in Figure 3. When we separately calculated the probabilities of membership, entry, and exit for each value the closeness variable can assume, we could plot how these probabilities change as closeness increases (see Figures 5 to 7).

When one moves along the horizontal closeness axis, one can see that the probabilities of both membership and entry are at first well below their overall averages but end far above them. Membership probabilities increase by a factor of 4.5 when values at a closeness of 0 are compared to values at closenesses in excess of 10. Entry probabilities rise even sevenfold. In contrast, exit probabilities start at 25 percent but decrease to less than one-third of that value. These numbers show that the effect of closeness on portfolio dynamics is not only statistically significant, but also has substantial economic implications.

To control for possible confounding variables in our analyses, we ran a number of regression analyses. Tables 3–5 show the outcomes. The first three columns of Tables 3–5 present the outcomes of the regression of the membership, exit, and entry

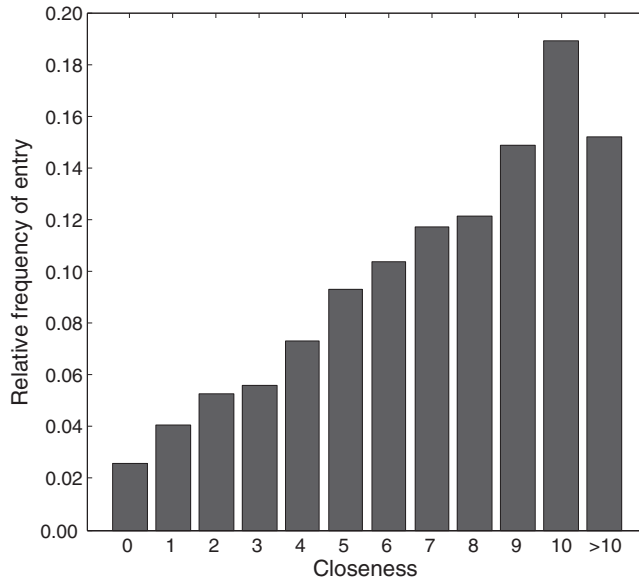


Figure 6. Probabilities of entry.

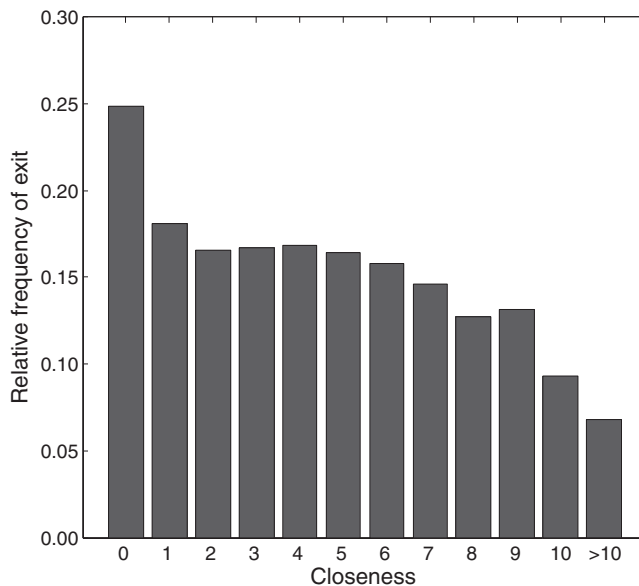


Figure 7. Probabilities of exit.

dummy variables on an industry's closeness to the portfolio of a region and a constant. The samples were restricted in the same way as in Table 2. Below the parameter estimates, we report robust standard errors.

The first column contains a linear probability model, which is simply an ordinary least-squares (OLS) regression of the dummy variables on the regressors. The signs of all parameter estimates are as expected. An industry's closeness to the regional portfolio increases the probability that it is already a member of that regional portfolio (see Table 3)

Table 3

*Regression Analyses of the Probabilities of Membership*

Membership Model	(1) OLS	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) Logit	(7) OLS
Closeness (PF)	0.038*** (0.000)	0.108*** (0.002)	0.178*** (0.003)	0.042*** (0.003)	0.013*** (0.001)	0.095*** (0.004)	0.021*** (0.001)
Log[emp(r)]				0.756*** (0.013)	0.113*** (0.002)	0.582*** (0.014)	0.086*** (0.002)
Log[emp(i)]				0.732*** (0.009)	0.106*** (0.001)	0.766*** (0.009)	0.109*** (0.001)
Closeness (non-PF)						-0.079*** (0.002)	-0.012*** (0.000)
Constant	0.181*** (0.002)	-0.889*** (0.007)	-1.457*** (0.012)	-13.637*** (0.152)	-1.566*** (0.018)	-12.031*** (0.154)	-1.299*** (0.019)
R <sup>2</sup>	0.077				0.195		0.211
Log-likelihood		-41037.5	-41047.0	-35336.9		-34653.3	
Number of observations	73,080	73,080	73,080	72,100	72,100	72,100	72,100

Note: Robust standard errors are shown in parentheses. Independent variables: closeness (PF): the number of closely related industries in the region, log[emp(i)]: the logarithm of the total Swedish employment in industry, log[emp(r)]: the logarithm of the total employment in the region, and closeness (non-PF): the number of closely related industries absent from the region. Dependent variable: the membership dummy variable is equal to 1 if an industry is found in the region's portfolio (i.e., if regional employment in the industry exceeds zero) and zero otherwise. The sample consists of all regional industries in 1969, 1974, 1979, 1984, 1989, and 1994. The column heads show the estimation techniques that were used.

Table 4

*Regression Analyses of the Probabilities of Entry*

Entry Model	(1) OLS	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) Logit	(7) OLS
Closeness (PF)	0.012*** (0.001)	0.084*** (0.003)	0.163*** (0.005)	0.097*** (0.006)	0.008*** (0.001)	0.110*** (0.007)	0.010*** (0.001)
Log[emp(r)]				0.283*** (0.029)	0.011*** (0.001)	0.228*** (0.031)	0.008*** (0.001)
Log[emp(i)]				0.450*** (0.017)	0.019*** (0.001)	0.468*** (0.018)	0.020*** (0.001)
Closeness (non-PF)						-0.025*** (0.005)	-0.002*** (0.000)
Constant	0.027*** (0.001)	-1.846*** (0.012)	-3.341*** (0.026)	-9.125*** (0.302)	-0.202*** (0.013)	-8.658*** (0.309)	-0.175*** (0.013)
R <sup>2</sup>	0.02				0.032		0.033
Log-likelihood		-10402.2	-10418.6	-9934.7		-9918.7	
Number of observations	52,226	52,226	52,226	51,246	51,246	51,246	51,246

Note: Robust standard errors are shown in parentheses. Independent variables: closeness (PF): the number of closely related industries in the region, log[emp(i)]: the logarithm of the total Swedish employment in an industry, log[emp(r)]: the logarithm of the total employment in the region, and closeness (non-PF): the number of closely related industries absent from the region. Dependent variable: the entry dummy variable is equal to 1 if the industry is found in the region's portfolio in year  $t + 5$  (i.e., if regional employment in the industry exceeds zero) but not in year  $t$ . The sample consists of all regional industries with zero employment in year  $t$  for 1969, 1974, 1979, 1984, 1989, and 1994. The column heads show the estimation techniques that were used.



Table 5

## Regression Analyses of the Probabilities of Exit

Exit Model	(1) OLS	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) Logit	(7) OLS
Closeness (PF)	-0.010*** (0.001)	-0.047*** (0.003)	-0.087*** (0.005)	-0.025*** (0.006)	-0.001* (0.001)	-0.048*** (0.007)	-0.004*** (0.001)
Log[emp(r)]				-0.336*** (0.025)	-0.047*** (0.003)	-0.258*** (0.027)	-0.036*** (0.004)
Log[emp(i)]				-0.453*** (0.016)	-0.065*** (0.002)	-0.455*** (0.016)	-0.066*** (0.002)
Closeness (non-PF)						0.034*** (0.004)	0.004*** (0.001)
Constant	0.208*** (0.004)	-0.791*** (0.015)	-1.287*** (0.026)	5.300*** (0.281)	1.155*** (0.039)	4.497*** (0.303)	1.044*** (0.043)
R <sup>2</sup>	0.012				0.051		0.053
Log-likelihood		-9229.7	-9229.2	-8845.9		-8814	
Number of observations	20,854	20,854	20,854	20,854	20,854	20,854	20,854

Note: Robust standard errors are shown in parentheses. Independent variables: closeness (PF): the number of closely related industries in the region, log[emp(i)]: the logarithm of the total Swedish employment in an industry, log[emp(r)]: the logarithm of the total employment in the region, and closeness (non-PF): the number of closely related industries absent from the region. Dependent variable: the exit dummy variable is equal to 1 if the industry is found in the region's portfolio in year  $t$  (i.e., if regional employment in the industry exceeds zero) but not in year  $t + 5$ . The sample consists of all regional industries with nonzero employment in year  $t$  for 1969, 1974, 1979, 1984, 1989, and 1994. The column heads show the estimation techniques that were used.

or, if it is not yet a member, that it will enter the region within the next five-year period (see Table 4). As is shown by the negative coefficient in Table 5, the probability that an industry will leave a region decreases with the number of industries to which it is closely related. The attractive feature of the OLS model is that the numeric interpretation of the estimates is immediately clear. For example, if we let the closeness value increase from 0 to 10, the probability of membership rises from 18.1 percent to 56.1 percent (see Table 3), the probability of entry rises from 2.7 percent to 14.7 percent (see Table 4), and the probability of exit drops from 20.8 percent to 10.8 percent (see Table 5). These values are remarkably close to the findings shown in Figures 5–7. OLS is, however, not an appropriate estimation technique for binary variables. Therefore, we also estimated probit and logit models. The coefficients of these models are not readily comparable.<sup>15</sup> However, the signs and significance levels of the parameters in both columns confirm the earlier findings of the OLS estimations.

The membership, entry, and exit dummy variables are likely to be affected by the overall sizes of both the industry and the region. After all, large industries will more often be members of a regional portfolio, and they are more likely to enter and less likely to exit

<sup>15</sup> The coefficients of probit and logit models are generally difficult to compare because the estimated effects change with changes in the regressor values. One way to compare parameter estimates across these models is to evaluate the marginal effects at the mean of the closeness variable. The estimates for the membership regressions of the probit and logit models are fairly similar at 0.0412 and 0.0355, respectively, with the OLS estimate in between. The estimates for the exit regressions are similarly comparable at -0.0184 and -0.0117, but are somewhat higher than the OLS estimates. The biggest difference is found in the estimates of average marginal effects on entry, where the probit model gives a value of 0.033 and the logit of 0.0075.

a region. Similarly, large regions typically host a large number of different industries and are able to attract new and to retain old industries more easily. To control for such effects, we added two new variables,  $\log[\text{emp}(r)]$  and  $\log[\text{emp}(i)]$  in column 4; these variables measure the log of the total manufacturing employment in region  $r$  (i.e., the size of the local economy) and of the total Swedish employment in industry  $i$  (i.e., the size of the industry in the whole of Sweden), respectively. To gain a rough notion of the sizes of the effects, we also estimated an OLS model, as is presented in column (5). Both variables have the expected effects in all three tables. However, the effects of our closeness indicator became smaller when we controlled for the overall size of a region and of an industry. This finding is in line with expectations because large regions can accommodate more industries, regardless of whether these industries are related or unrelated to a specific industry. Similarly, large industries will, *ceteris paribus*, be present in many regions. As is shown in Table 1 therefore, both the size of a region and the size of an industry correlate positively with the probabilities of membership and, if the sample is duly restricted (i.e., if one takes into consideration that an industry must be absent to be able to enter a region and present to be able to exit a region) with entry probabilities, but these variables correlate negatively with exit probabilities. Yet the influence of closeness to the regional portfolio remains strongly significant for the probabilities of membership, entry, and exit alike.

In columns (6) and (7), we added a final variable, *closeness (non-PF)*. Again, the OLS estimates in column (7) should be taken only as indicative. Whereas the closeness (PF) variable measures the closeness of an industry to a region's portfolio, the closeness (non-PF) variable measures the closeness of an industry to all industries that are *absent* from the region's portfolio. In other words, we assessed what happens when an industry has to get by without the local presence of a number of industries to which it is strongly related. Table 3 shows that the effect on the probabilities of membership is substantial. If industry  $i$  is strongly related to industries that are absent from region  $r$ , it is likely also to be absent from this region itself. Table 4 shows that such missing related industries also lead to lower entry rates. Table 5 completes this picture by showing that the absence of a large number of related industries may lead industries to leave, even though there may still be many related industries in the region. In fact, this tendency could result in a domino effect, in which the departure of a small number of industries could lead to a complete dismantling of a larger technological cluster in the region. In the next section, we take a closer look at the region of Linköping, wherein, after such a domino phenomenon, the entire local cluster of textile industries abandoned the region.

To summarize, the regression analyses confirm the three regularities that we identified in the previous section. The closeness of an industry to a regional portfolio has important consequences for the technological cohesion of a region—in terms of membership probabilities—and for the evolution of its industrial structure in terms of both entering and exiting industries.

## Revealed Relatedness in Case Study Research: Linköping's Industrial Transformation

In the introduction, we claimed that information on how industries are related to one another can support research that uses case studies to investigate the dynamics of structural change in individual regions. In this section, we illustrate this claim by using the Linköping region, which is located roughly 200 kilometers southwest of Stockholm, as an example.

The choice of Linköping is arbitrary, but the region is known to have gone through substantial structural change, making it an interesting candidate for case study analysis. Linköping is, by Swedish standards, a midsized region, and it is home to one of the major universities in the country. Its population increased from 85,000 inhabitants in 1970 to 101,000 in 2000. Historically, the region has been known primarily for its specialization in traditional manufacturing and aviation technology. More recently, it has become associated with a number of high-tech information technology industries and houses an important science park.

Turning to our newly developed toolbox, Figure 8 shows Linköping's manufacturing portfolio in industry space and its evolution between 1970 and 2000. The basic network is the same as the one depicted in Figure 1, but the interpretation of the colors of the nodes is different. White circles symbolize industries that were absent from Linköping for the entire period between 1970 and 2000. Blue circles represent industries that were present in all decades between 1970 and 2000. Green upward- and red downward-pointing triangles represent industries that entered and exited the region, respectively, somewhere between 1970 and 2000.

258 The depicted position of Linköping's manufacturing economy in industry space suggests that the region's manufacturing sector is clearly cohesive. The region's strong presence in the metal and machinery industries stands out as a cluster of blue nodes in the lower left corner of industry space, in contrast to the large parts of industry space that are dominated by white nodes, wherein Linköping never developed any activities.

This apparent cohesion is confirmed by Figure 9, which contains graphs that are analogous to Figure 4 but now depict only the structural transformation in Linköping. Consider first the solid line, which plots the level of cohesion of Linköping's portfolio, and the dotted line, which displays the average closeness of Linköping's portfolio to the industries that are absent from the region. The portfolio line is always above the nonportfolio line, confirming industrial cohesion. However, Linköping's strong industrial cohesion is a rather recent phenomenon. The solid line started well below the Swedish average of just over four related industries for each portfolio member, and it was very close to the dotted line. Toward the 1990s, however, Linköping's industrial cohesion quickly surpassed the Swedish average, and the distance between the solid and dotted lines substantially increased.

To investigate what happened here, we need to look at the industries that entered and exited the region. In Figure 8, these entrances and exits are depicted by the upward- and downward-pointing triangles. In this graph, darker shadings indicate that the exit or entry event occurred earlier in time. All early entrants in the Linköping economy (narrow fabrics, computers, communication, metal machinery, and household appliances) can be found in the heart of the machinery-related industries, reinforcing Linköping's specialization. Exiting industries, in contrast, are, in general, peripheral to the technological core of the region. The closeness of (in particular, early) entrants (green dashed line, upward triangles) to Linköping's portfolio and the relative isolation of the exiting industries (red dashed line, downward triangles), which together caused Linköping's industrial portfolio to grow more cohesive over time, is confirmed in Figure 9.

Linköping also seems to have undergone a cascade of exits in a cluster of textile- and wood-related industries. As in many of Sweden's textile-producing regions, the textiles cluster was hit hardest in the 1970s, when several of its industries declined and left the country. Figure 8 shows how the early exit of a number of these industries was followed by exits in other industries of the cluster, which had become peripheral to the region's remaining portfolio as a result of this early exodus: after the initial collapse of the shirts,

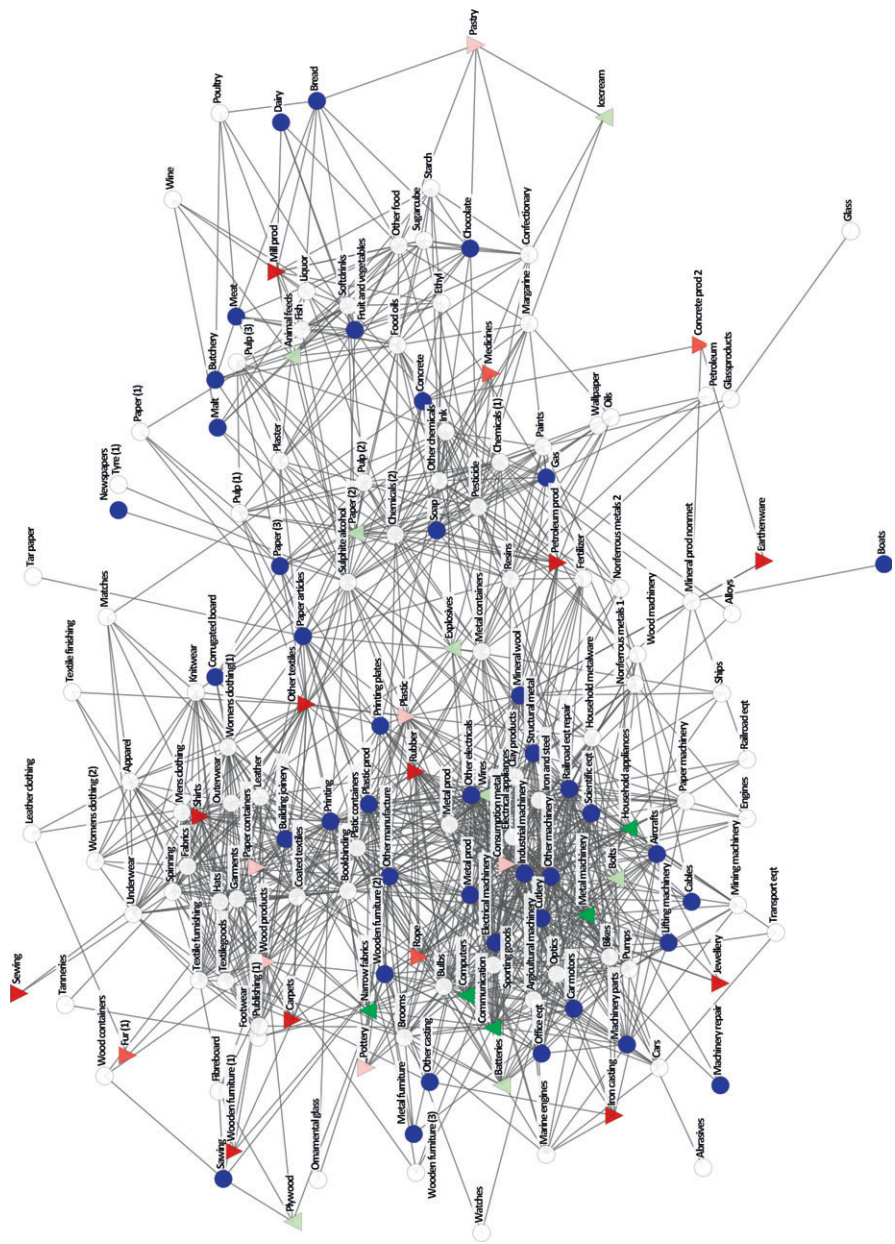


Figure 8. The average industry space in Sweden, 1969–2002, with the addition of the production structure of Linköping. Blue circles: industries persistently present in region. Red downward-pointing triangles: industries exiting the region between 1970 and 2000. Green upward-pointing triangles: industries entering the region between 1970 and 2000. White circles: not part of the regional portfolio in both 1970 and 2000. Shades of color indicate the following. Dark: change taking place in the 1970s, medium: change taking place in the 1980s, and light: change taking place in the 1990s.

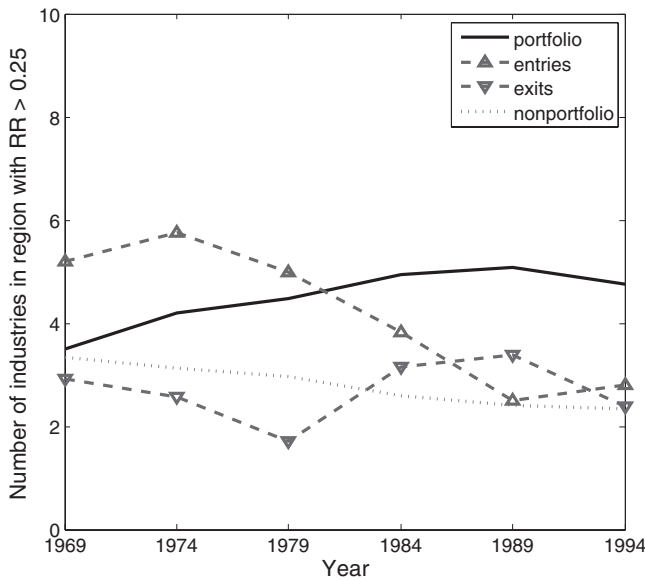


Figure 9. The evolution of the closeness measure for the Linköping region.

All lines depict averages for regional industries in Linköping. Solid line: the closeness of portfolio members to Linköping's portfolio as a whole; dotted line: the closeness of absent industries to Linköping's portfolio; dashed line (upward triangles): the closeness of entering industries to Linköping's portfolio; dashed line (downward triangles): the closeness of exiting industries.

other textiles, and carpet manufacturing industries, the fur and rope industries vanished, followed by the production of wood products and paper containers. By 2000, Linköping had all but lost its complete cluster of textile and wood industries.<sup>16</sup>

The foregoing description shows that industry space analyses of the Linköping region can identify interesting cases of coevolving local industries. Apart from the cascading exits of textiles and wood industries, for instance, the region's core specialization in machinery-related industries seems to have been strengthened by entries in related yet technologically more advanced industries, like the computer and the communication industries. This finding suggests that Linköping's successful diversification may have depended on the linking of these new industries to the old local manufacturing specialization. This may provide an interesting starting point for case study research, which could investigate whether such interdependencies may have been rooted in linkages between firms in the new industries and firms from Linköping's traditional manufacturing base or whether institutions or labor markets were shared. In any event, a visual analysis of industry space can help localize likely hot spots of interindustry interaction in the structural transformation of a region that merit closer scrutiny by qualitative research methods. Moreover, knowledge of which industries are strongly linked to the protagonists of structural change in a specific region can help sharpen the focus and delimit the scope of a case study design.

<sup>16</sup> This phenomenon may not be particular to Linköping's economic evolution. In fact, the successive exits of textile industries may also have been due to the decline of the sector in the entire Swedish economy. In that case, the industry space analysis should be applied not only at the regional level but at the level of the national economy.



## Conclusions

In this article, we analyzed structural change in the industrial portfolios of Swedish regions from an evolutionary economic perspective. In line with evolutionary reasoning, regional diversification emerged as a strongly path-dependent process. Regions diversify by branching into industries that are related to their current industries. In particular, industries are more likely to enter a region if they are technologically close to the regional portfolio. However, in general, industries that enter a region are less related to the local industrial portfolio than the average technological proximity among existing portfolio members. Consequently, entry typically lowers a region's technological cohesion by adding new variety. In this sense, it fulfills a role that is analogous to evolutionary *mutations*. The probabilities of exit, in contrast, increase as industries hold technologically more peripheral positions in a region's portfolio. Exit thus increases the technological cohesion of regions, which conforms to the variety-reducing effect of *selection*. However, industries are also more likely to leave if technologically related industries are missing from the region. As a consequence, the exit of one industry can set a cascading sequence of exits into motion, leading to the departure of complete technological clusters. An example of such domino effects was observed in the Linköping region, which lost its entire textile and wood industry cluster.

Revealed relatedness and industry space also provide powerful tools that can be used in case study analysis and regional policymaking. By depicting a regional portfolio in industry space, policymakers may identify future threats and opportunities for their regions. In particular, our analyses suggest that it is difficult to attract new industries to a region if they are technologically distant from the present local activities. Moreover, even if they can be persuaded to enter, the high exit probabilities of technologically peripheral industries suggest that these industries are unlikely to last long. If new activities are at least somewhat related to existing activities, stimulating knowledge-transfer mechanisms (e.g., entrepreneurship, labor mobility, networking) has a better chance of effectively embedding these new industries in regional production structures. However, the fact that we found evidence of the self-selection of industries into regions that host a substantial amount of related economic activities suggests there may be only limited justification for targeted industrial policy. For industries that are related to the current mix of industries but that have not yet entered the local economy, the region may be ill suited for reasons that are not studied in an industry space analysis. It would therefore be advisable to investigate these potential entrants more closely and find out why firms in these industries apparently shun the region. If it turns out that there are bottlenecks that can be remedied, policy initiatives aimed at removing these bottlenecks are warranted.

In terms of future research, the relatedness perspective opens up an entire new research agenda. First, the systematic evidence presented here shows that new growth paths in regions do not start from scratch but are strongly rooted in the historical economic structure of a region. This could be an interesting perspective for the study of the rise of spatial clusters, which has recently drawn much attention (see, e.g., Menzel and Fornahl 2010). It could also help economic geographers to understand better how old industrial regions restructure and adjust their economies over time, a topic that ranks highly on scientific and political agendas in times of economic crisis. However, a complete understanding of regional growth paths and regional resilience requires knowledge of whether, and how, the economic structure of a region affects the region's future development. One could, for instance, investigate how the coherence of a regional portfolio affects the region's growth potential in periods of economic growth and in periods of economic decline. Second, there is a strong need to determine mechanisms through which the



process of regional branching operates. Boschma and Frenken (forthcoming) mentioned four knowledge-transfer mechanisms through which new industries can connect to existing industries that operate mainly (but not exclusively) at the regional level: the diversification of firms, entrepreneurship in the form of spinoffs, labor mobility, and networking. However, the importance of these mechanisms in the development of new regional growth paths still needs to be explored. Moreover, Dumais, Ellison, and Glaeser (2002) and Barrios, Bertinelli, Stroble, and Teixeira (2005) showed that at the plant level, plant closures reinforce the geographic concentration of an industry, whereas the birth of new plants tends to lead to more spatial dispersion of an industry. It would be interesting to investigate whether such microlevel dynamics also affect the overall cohesion of local economies in different ways. Third, more in-depth analyses of the implications of the entry of new industries that bridge two technology clusters in a region are needed. Although it is plausible that these industries have a large impact on long-term regional development, so far empirical evidence is lacking. Fourth, our study focused on regional portfolios to the neglect of interregional effects. Spillovers between related industries are probably not restricted to a region but will also be manifest between neighboring or highly connected regions. Fifth, when we examined how technological relatedness shapes the process of creative destruction in regional economies, we took the relatedness structure of the economy as given. However, the RR methodology supports a more dynamic approach to relatedness, in which industry space is conceptualized as a network structure that changes under the influence of technological shifts. A dynamic conceptualization of relatedness raises an entire set of questions. For instance, do general-purpose technologies like ICT result in a rewiring of industry space? If so, what are the spatial consequences one would expect? Finally, it is not self-evident that industries that are strongly related in one country are also strongly related in another. Different historical conditions and institutions may lead to different configurations of industry space. We strongly believe that answering these and other questions is crucial for the further advancement of an evolutionary approach in economic geography.

## References

- Barrios, S.; Bertinelli, L.; Stroble, E.; Teixeira, A. C. 2005. The dynamics of agglomeration: Evidence from Ireland and Portugal. *Journal of Urban Economics* 57:170–88.
- Barro, R., and Sala-i-Martin, X. 1995. Convergence across states and regions. *Brookings Papers on Economic Activity* 1:107–82.
- Bathelt, H., and Boggs, J. S. 2003. Towards a reconceptualization of regional development paths: Is Leipzig's media cluster a continuation of or a rupture with the past? *Economic Geography* 79:265–93.
- Bishop, P., and Grippaios, P. 2010. Spatial externalities, relatedness and sector employment growth in Great Britain. *Regional Studies* 44:443–54.
- Borgatti, S. P. 2002. *NetDraw: Graph visualization software*. Lexington, Ky.: Analytic Technologies.
- Boschma, R., and Frenken, K. Forthcoming. Technological relatedness and regional branching. In *Dynamic geographies of knowledge creation and innovation*, ed. H. Bathelt, M. P. Feldman, and D. F. Kogler. London: Routledge, Taylor and Francis.
- Boschma, R. A., and Iammarino S. 2009. Related variety, trade linkages and regional growth in Italy. *Economic Geography* 85:289–311.
- Boschma, R. A., and Wenting, R. 2007. The spatial evolution of the British automobile industry: Does location matter? *Industrial and Corporate Change* 16:213–38.

- Bryce, D. J., and Winter, S. G. 2009. A general interindustry relatedness index. *Management Science* 55:1570–85.
- Carlsson, B., and Stankiewicz, R. 1991. On the nature, function and composition of technological systems. *Journal of Evolutionary Economics* 1:93–118.
- De Groot, H.; Poot, J.; and Smith, M. J. 2009. Agglomeration externalities, innovation and regional growth: Theoretical perspectives and meta-analysis. In *Handbook of regional growth and development theories*, ed. R. Capello and P. Nijkamp, 256–81. Cheltenham, U.K.: Edward Elgar.
- Dosi, G. 1984. *Technical change and industrial transformation: The theory and an application to the semiconductor industry*. London: Macmillan.
- Dumais, G.; Ellison, G.; and Glaeser, E. L. 2002. Geographic concentration as a dynamic process. *Review of Economics and Statistics* 84:193–204.
- Duranton, G., and Puga, D. 2001. Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review* 91:1454–77.
- Essletzbichler, J. 2007. Diversity, stability and regional growth in the United States, 1975–2002. In *Applied evolutionary economics and economic geography*, ed. K. Frenken, 203–29. Cheltenham, U.K.: Edward Elgar.
- Fan, J. P. H., and Lang, L. H. P. 2000. The measurement of relatedness: An application to corporate diversification. *Journal of Business* 73:629–60.
- Farjoun, M. 1994. Beyond industry boundaries: Human expertise, diversification and resource-related industry groups. *Organization Science* 5:185–99.
- Frenken, K., and Boschma, R. A. 2007. A theoretical framework for evolutionary economic geography: Industrial dynamics and urban growth as a branching process. *Journal of Economic Geography* 7:635–49.
- Frenken, K.; Van Oort, F. G.; and Verburg, T. 2007. Related variety, unrelated variety and regional economic growth. *Regional Studies* 41:685–97.
- Glaeser, E. L. 2005. Reinventing Boston: 1630–2003. *Journal of Economic Geography* 5:119–53.
- Glaeser, E. L.; Kallal, H. D.; Scheinkman, J. A.; and Schleifer, A. 1992. Growth in cities. *Journal of Political Economy* 100:1126–52.
- Grabher, G. 1993. The weakness of strong ties: The lock-in of regional development in the Ruhr area. In *The embedded firm*, ed. G. Grabher, 255–77. London: Routledge.
- Hall, P. G., and Preston, P. 1988. *The carrier wave: New information technology and the geography of innovation 1846–2003*. London: Unwin Hyman.
- Hausmann, R., and Klinger, B. 2007. The structure of the product space and the evolution of comparative advantage. Working paper no. 146, Center for International Development, Harvard University, Cambridge, Mass.
- Henderson, J. V.; Kuncoro, A.; and Turner, M. 1995. Industrial development in cities. *Journal of Political Economy* 103:1067–85.
- Hidalgo, C. A.; Klinger, B.; Barabási, A.-L.; and Hausmann, R. 2007. The product space conditions the development of nations. *Science* 317:482–87.
- Hohenberg, P. M., and Lees, L. H. 1995. *The making of urban Europe 1000–1994*. Cambridge, Mass.: Harvard University Press.
- Jacobs, J. 1969. *The economy of cities*. New York: Vintage Books.
- Klepper, S. 2007. Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry. *Management Science* 53:616–31.
- Krugman, P. R. 1991. Increasing returns and economic geography. *Journal of Political Economy* 99:483–99.

- Markusen, A. 1985. *Profit cycles, oligopoly and regional development*. Cambridge, Mass.: MIT Press.
- Marshall, M. 1987. *Long waves of regional development*. London: Macmillan.
- Martin, R., and Sunley, P. 2006. Path dependence and regional economic evolution. *Journal of Economic Geography* 6:395–437.
- . 2010. The place of path dependence in an evolutionary perspective on the economic landscape. In *The handbook of evolutionary economic geography*, ed. R. Boschma and R. Martin, 62–92. Cheltenham, U.K.: Edward Elgar.
- Menzel, M. P., and Fornahl, D. 2010. Cluster life cycles: Dimensions and rationales of cluster evolution. *Industrial and Corporate Change* 19:205–38.
- Neffke, F. 2009. Productive places. The influence of technological change and relatedness on agglomeration externalities. PhD thesis, Utrecht University, Utrecht, the Netherlands.
- Neffke F. M. H., and Svensson Henning, M. 2008. Revealed relatedness: Mapping industry space. Working Paper Series 08.19, Papers in Evolutionary Economic Geography, Utrecht University, Utrecht, the Netherlands.
- 264 Neffke, F.; Svensson Henning, M.; Boschma, R.; Lundquist, K.-J.; and Olander, L.-O. 2011. The dynamics of agglomeration externalities along the life cycle of industries. *Regional Studies* 45:49–65.
- Nooteboom, B. 2000. *Learning and innovation in organizations and economies*. Oxford, U.K.: Oxford University Press.
- Norton, R. D. 1979. *City life-cycles and American urban policy*. New York: Academic Press.
- Norton, R. D., and Rees, J. 1979. The product cycle and the spatial decentralization of American manufacturing. *Regional Studies* 13:141–51.
- Rigby, D. L., and Essletzbichler, J. 1997. Evolution, process variety, and regional trajectories of technological change in U.S. manufacturing. *Economic Geography* 73:269–84.
- Schumpeter, J. A. 1939. *Business cycles: A theoretical, historical and statistical analysis of the capitalist process*. New York: McGraw-Hill.
- Scott, A. J. 1988. *New industrial spaces: Flexible production organization and regional development in North America and Western Europe*. London: Pion.
- Simmie, J., and Carpenter J., eds. 2007. Path dependence and the evolution of city regional development. Working Paper Series No. 197, Oxford Brookes University, Oxford, U.K.
- Storper, M., and Walker, R. 1989. *The capitalist imperative: Territory, technology and industrial growth*. New York: Basil Blackwell.
- Teece, T. D.; Rumelt, R.; Dosi, G.; and Winter, S. 1994. Understanding corporate coherence: Theory and evidence. *Journal of Economic Behaviour and Organization* 23:1–30.

## Appendix

### Product Portfolio

The original data were obtained from Statistics Sweden. Our database contains information on products that are produced in Swedish manufacturing plants. We imputed a translation from these product codes to industry codes by matching the different product classification systems (CCC and KN/HS) to the industry codes of the plants on the basis of the fact that plants are classified into the industry in which they generate the most output. Between 1969 and 2002, some 57 percent of all the plants were active in only one industry. Most other plants, some 22 percent, produced products in 2 industries. The data collection procedure for product information has changed over time. Between 1969 and 1989, the sample included all plants with at least 5 employees in manufacturing activities. Between 1990 and 1994, plants with at least 5 employees that belonged to manufacturing

firms with at least 10 employees were included. From 1997 onward, information on manufacturing firms with at least 20 employees was included in our data set, as was information on manufacturing plants with at least 20 employees that belonged to service firms. Because of the changing sampling regime and the shift of the economy from manufacturing to services, the number of registered plants in the database decreased over time. Nevertheless, we still have information on the production structures of some 2,000 plants even in the last year, 2002.

### Regional Industrial Portfolio

The original data set contained plant-level data, which were obtained from Statistics Sweden. From this data set, we used information on the SNI (industry) codes of the plants and their location in one of the 70 functional regions. The sample had, over time, the following composition: between 1968 and 1989, Swedish plants with at least 5 employees are included in the data set. From 1990 to 2002, plants with at least 5 employees that belonged to firms with at least 10 employees were included. In the mid-1990s, the Swedish industry classification switched from the SNI69 system to the SNI92 system. For a large number of plants in the 1990s, both classification codes were made available to us. We used these plants to impute a translation from SNI92 codes to SNI69 codes. In particular, as a translation, we used the SNI69 code that was most often provided in conjunction with a particular SNI92 code. In the vast majority of cases, the best translation was immediately clear from this strategy, and there was often only one SNI69 that could be matched to a particular SNI92 code. The remaining industries, 11 in total, were translated manually.

The level of analysis was the regional industry, that is, the presence or absence of a specific industry in a specific region. The entry of an industry into a region occurred if, in the previous period, there was no economic activity in this industry in the region. More specifically, an industry entered a region if it obtained at least one plant in the region with more than five employees. Smaller plants are not observable in our data. Some industries might have therefore been present but remained undetected. Industries could thus enter because (1) a new plant with at least five employees was set up in the region, (2) an existing small plant grew larger than four employees, (3) an existing (large) plant from another region relocated to the new region, or (4) an existing (large) plant changed from its old industry to the industry at hand. Similarly, for an industry to exit a region, its smallest plant in the region had either to (1) close down, (2) fall below the five-employees threshold, (3) migrate, or (4) change its production to another industry.

