The impact of relatedness and knowledge transfer on growth and structural change of firms and regions

Matte Hartog

Hartog, M.

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The impact of relatedness and knowledge transfer on growth and structural change of firms and regions

Het belang van gerelateerdheid en kennisdiffusie voor groei
en structurele verandering van bedrijven en regio's

(met een samenvatting in het Nederlands)

Proefschrift

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Matte Hartog

geboren op 7 november 1987 te Zwolle

Promotor: Prof. dr. R.A. Boschma

Copromotoren: Dr. A. Morrison
Dr. F.M.H. Neffke

"Our remote ancestors did not expand their economies much by simply doing more of what they had already been doing: piling up more wild seeds and nuts, slaughtering more wild cattle and geese, making more spearheads, necklaces, burins and fires. They expanded their economies by adding new kinds of work. So do we." (Jane Jacobs, 1969, p. 49)

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1.
Introduction

1.1 Background

In December 2014, Detroit got out of the largest municipal bankruptcy that had ever been filed in the United States. Whereas the city had evolved into a thriving metropolitan area by the mid-20th century, it captured headlines around the world when it filed for bankruptcy in 2013. Once an industrial powerhouse that gave birth to the automobile industry in the Unites States, it had, as the Daily Mail (2013) put it, developed into a "Motor city run out of gas". Given the city's reliance on a single industry, the prospects of renewing itself are uncertain. As The Guardian (2010) writes: "amid the ruins of the Motor City it is possible to find a first pioneer's map to the post-industrial future that awaits us all. So perhaps Detroit can avoid the fate of the lost cities of the Maya and rise again like the phoenix that sits, appropriately, on its municipal crest." Not only Detroit but many regions in the world are characterized by deep specializations, ranging from computer-related activities in Santa Clara Valley (Silicon Valley) to lighters production in Wenzhou in China, all of which face the same danger as Detroit once the demand for their products drops.

Detroit's experience highlights the importance of the entry and development of new local activities and capabilities for economic development of regions. In the long run, regions depend on their ability to foster new activities in order to offset decline and destruction in other parts of their economies. This importance of renewal was already highlighted in the 1950s and 1960s by important figures in development economics such as Lewis (1955), Rostow (1959), Kuznets (1966) and Kaldor (1967). Joseph Schumpeter once identified this process of creative destruction as the driving force behind economic development.

However, renewal is not straightforward. There is increasing evidence that diversification of economies happens step-by-step through the emergence of new industries that are related to ones that are already present (Hidalgo et al., 2007; Neffke et al., 2011). New industries are likely to grow out of existing industries because of the re-combination of existing capabilities. For instance, Klepper and Simons (2000) showed that the radio industry gave birth to the television industry through diversifiers and spinoffs. Hence, relatedness is a key aspect of structural change, linking new industries to pre-existing ones.

The fact that new activities tend to grow out of existing ones is a key insight of the evolutionary theory of the firm (Nelson and Winter, 1982). Firms operate on the basis of routines that develop over time. Those routines are not only cumulative but also tacit, which makes it hard for other firms to imitate them. Moreover, they are the foundation of the capabilities of firms (Wernerfelt, 1984; Barney, 1991) that allow firms to be competitive. Thus, one's existing capabilities determine the possible directions to diversify into. For instance, automobile producers are better able to diversify into motorcycles than grain producers. They are also more likely to do so because of the fundamental uncertainties they face, which is why they tend to search for new opportunities in the vicinity of their existing capabilities, or what Nelson and Winter call 'local search'. Hence, firm growth can be conceived as a process of related diversification, representing a path-dependent process rooted in one's history (Penrose, 1959).

Building upon these micro insights to explain macro findings at the regional level is the key aim of the “evolutionary economic geography” approach that has emerged over the past two decades (Boschma and Lambooy, 1999; Boschma and Frenken, 2006; Boschma and Martin, 2010). This approach aims to understand the spatial distribution of routines over time and how this relates to uneven economic development in space. Because its explananda start from the routines that exist at the organizational level, the organization is the key unit of analysis. Within the same context, as in a local environment where firms deal with the same policy makers and regulations, there still is much heterogeneity among firms because each firm has inherited routines that are unique to its own past. For instance, the amount of local networking has been shown to differ widely among local firms that operate within the same sector and region (Giuliani, 2007). At the same time, a firm can apply its routines in different contexts. Hence, there are no firms with just place-specific routines (Boschma and Frenken, 2009). Thus, this evolutionary understanding of regional development rests upon how the routines of firms, and the knowledge and capabilities that they underlie, diffuse across space.

From this micro-based perspective, of key interest are the mechanisms that facilitate the transfer of routines and capabilities between organizations. Routines and capabilities do not automatically diffuse between organizations due to their tacit nature. Rather, they diffuse through mechanisms, particularly spillovers, spinoffs, labor mobility, mergers and acquisitions, and inter-organizational networks. This PhD thesis investigates how these mechanisms, in conjunction with relatedness, induce growth and structural change of local economies and plants. The key unit of interest is the composition of activities within regions and plants. To what extent are these compositions coherent as in consisting of related activities? How does the composition of activities affect the growth of activities? And how do new activities develop in certain compositions of activities and through which mechanisms? In investigating these questions, this PhD thesis starts the investigation at the regional level and gradually moves down the level of analysis, ending at the level of the economic establishment and individual worker.

1.2 Research questions and outline

Below follows an outline of the research questions that are investigated in each of the chapters.

Chapter 2

In the agglomeration economies literature, there has been a long-standing debate on how the composition of economic activities within regions affects the growth of these activities. Marshall (1920) argued that regional compositions of similar activities are beneficial for growth, whereas Jacobs (1969) argued that one needs a diversity of activities. Frenken et al. (2007) distinguished among diversity of related activities and diversity of unrelated activities within regions. These authors showed that having a mix of related industries in regions, or ‘related variety’, is what drives regional employment growth, rather than specialization or diversity as such. They attribute this finding to the fact that in such a mix of related activities/ regional economies composed of different yet related activities there is neither too much cognitive similarity among local activities (with little to learn from one another) nor too little cognitive similarity (which would hamper learning due to a lack of mutual understanding).

However, Frenken et al. (2007) do not consider sector specificities that might condition the impact of related variety on growth. A plausible hypothesis is that only related variety among high-tech industries has a positive impact on regional employment growth. Such industries mainly draw upon and recombine complex knowledge from different industries to produce innovations, particularly radical innovations (Antonelli, 2004). As such, they are particularly dependent on cross-industry spillovers and learning, which is why they are more likely to benefit from related variety. Hence, the technological intensity of an industry might condition the impact of related variety on regional employment growth. The following research question is addressed in Chapter 2:

To what extent is the impact of related variety on regional employment growth conditioned by the technological intensity of the local industries concerned?

To investigate this, Finnish data between 1993 and 2006 are used. During this period, the economy of Finland changed into a high-tech economy, with an increasing variety of high-tech industries. In the analysis, system GMM estimators are used to deal with endogeneity issues related to omitted variable bias and reverse causality when investigating the impact of related variety on regional growth.

Chapter 3

To better understand how the composition of activities within a region affects development, it is important to understand how linkages between organizations and their activities come into being and how they change over time. Recently, a number of theoretical accounts of the spatial evolution of inter-organizational networks (Gluckler, 2007; Ter Wal and Boschma, 2009) and how the evolution of networks affects development (e.g. Boschma and Frenken, 2010) have appeared. One of the key hypotheses proposed in this literature is that proximity fosters tie formation between organizations, but, at the same time, hampers development when there is too much of it. This has been referred to as the proximity paradox regarding networks and growth (Broekel and Boschma, 2012). To investigate such a hypothesis, instead of assuming that inter-organizational ties exist *a priori* as in Chapter 2, one needs to measure and analyse the formation of linkages directly. Few studies in economic geography have done this so far, exceptions being Balland (2012) and Ter Wal (2011). This requires one to investigate the importance of factors at the dyad level, particularly relatedness and other forms of proximity, in conjunction with factors at the node level (such as absorptive capacity) and the structural network level. In particular, the existing network structure may be driving future tie formation. For instance, a tendency towards triadic closure implies that partners of an organization are more likely to tie amongst themselves and become partners as well. A self-reinforcing and path-dependent process would then be driving the network and reinforcing the network structure (Nelson and Winter, 2002), which might eclipse the effect of proximity on tie formation. Chapter 3 investigates the following research question:

What determines the creation of knowledge transfer ties between organizations?

The empirical analyses in this chapter focus on the knowledge network in the Dutch aviation industry as observed in 2008. 59 aviation organizations out of a population of 64 have been interviewed to gather the data. Exponential random graph models are applied to investigate tie formation. These models represent a new set of network analysis techniques developed in mathematical sociology (Snijders et al., 2006; Robins et al., 2006, 2007; Wang et al., 2012) that are increasingly used by scholars across scientific disciplines particularly for their ability to determine the importance of factors at the dyad in conjunction with factors at the node and structural network level.

Chapter 4

In addition to inter-organizational networks, two mechanisms that link organizations and their activities together are mergers/acquisitions (M&As) and spillovers. The clustering of similar activities and the benefits thereof are traditionally attributed to spillovers or so-called Marshall-Arrow-Romer (MAR) externalities. However, an even more important driver of clustering and productivity increases may be M&A activity. Both M&As and spillovers allow firms to acquire capabilities from similar firms. If learning benefits from similar capabilities would be present, they might reinforce existing capabilities and reduce the chance of diversification into new activities. However, at the same time, MAR externalities might reduce the performance of local firms due to competition effects, such as demand for the same local resources. Furthermore, MAR externalities differ from M&As as the latter also gives firms access to the routines that exist at the level of the organization. For instance, Hoetker and Agarwal (2007) found that in the dissolution of firms in the disk drive industry, more knowledge to surviving firms was transferred from acquired firms than from displaced employees. This is because the former also gave acquirers access to what Hoetker and Agrawal call the "template" of the firm (reflecting Nelson and Winter's (1982) routines). Hence, M&As, because they also give access to routines, might help firms in better implementing newly acquired capabilities and improving their current activities. As a result, rather than MAR externalities, intra-industry M&As might foster the spatial clustering of an industry over time. Chapter 4 investigates this by addressing the following research question:

Compared to the benefits of co-location with firms in the same industry, to what extent do intra-industry mergers and acquisitions increase the performance of firms? And to what extent do intra-industry mergers and acquisitions foster the

spatial clustering of an industry over time?

This is investigated for the banking industry in The Netherlands between 1850 and 1993. During this period, the banking industry increasingly clustered in Amsterdam. For each bank that existed during this period, the location of the headquarters as well as the year of entry (if after 1850) and exit (if before 1993) is known. Also known is whether exits happen through mergers with or acquisitions by other banks. Hence, the performance of individual banks, measured by their survival rate, and the spatial evolution of the banking industry can be analysed for over a period of 143 years.

Chapter 5
Having investigated how regional compositions of activities come into being and affect organizational performance, the next question is which agents are most likely to change the regional composition of activities. There is increasing evidence that new activities tend to grow out of existing activities (Klepper and Simons, 2000; Bathelt and Boggs, 2003; Glaeser, 2005; Klepper, 2007; Boschma and Wenting, 2007), and thus, that economies tend to diversify into activities that require similar capabilities as the activities they currently host (Neffke et al., 2011; Hidalgo et al., 2007). These findings correspond to the evolutionary logic that the re-combination of existing capabilities gives birth to new activities. Yet, no systematic evidence exists on who diversify economies, that is, which agents tend to induce related diversification and reinforce specializations of regional compositions of activities, and which agents tend to induce unrelated diversification or structural change. The contribution of Chapter 5 is to investigate structural change of local economies from such a micro-perspective. It addresses the following research question:

Who are the main agents of structural change in a region?

Among the agents, one can distinguish between existing firms and new firms by entrepreneurs. Furthermore, these can originate from within the region and from elsewhere. Schumpeterian theories regard entrepreneurs as the main agents of change. Also, evolutionary reasoning implies that change is unlikely to come from within regions because when existing local activities give birth to new activities, such new activities tend to employ similar capabilities because they inherit routines from the parent source. Hence, such new activities are strongly related to existing activities. Thus, the key hypothesis is that one needs new influx from elsewhere, particularly entrepreneurs, for structural change.

The second contribution of Chapter 5 is to explicitly distinguish, theoretically and empirically, industrial change from structural change of local economies. The former is concerned with changes in the activity mix of regions, whereas the latter is concerned with changes of the local capabilities that underlie activities. Most of the existing, classical work on structural change defines structural change as a change in the activity mix of economies (e.g. Pasinetti 1981; Paci and Pigliaru, 1997; Fagerberg, 2000). However, from an evolutionary perspective, which explicitly distinguishes routines and capabilities of firms from the activities that employ them, changes in the activity mix would not necessarily constitute structural change. For instance, a shift in a region's specialization from shoe making to boots making would constitute a change in the mix of activities, but not in the capability base of the region. Hence, separating industrial change from structural change is necessary to determine how much structural change each agent induces.

This is investigated using Swedish matched employer-employee data that cover all workers, plants and firms in the economy for each year between 1994 and 2010. For each worker, personal characteristics such as age, wage and occupation are known, as well as the plants and firms they are affiliated to and the industries plants operate in. Annual inter-industry labor flows are used to measure relatedness between industries. This inter-industry relatedness matrix is used to measure structural change and separate it from industrial change. This, in turn, allows quantifying the amount of industrial and structural change each agent type induces.

Chapter 6

Having investigated which agents induce structural change at the regional level, the next question is how such change happens at the organizational level, going down further to the micro level. Not only at the regional level, but also at the organizational level, abundant evidence exists that new activities tend to grow out of existing activities. Following Penrose (1959), many studies have found that renewal within firms mimics related diversification as firms capitalize on the capabilities they possess (an overview is given by Barney et al., 2011). Much is thus known about how diversification within organizations takes place, but, again, less is known about which agents induce which kind of diversification moves. The contribution of Chapter 6 is to adopt such a micro-perspective by investigating the importance of labor mobility of managers and technicians as a mechanism of capability diffusion between plants.

The hypothesis is that the influx of new capabilities through labor mobility increases the chance of diversification into new activities. Employees accumulate capabilities at work which are often embodied within the person and which are hard to codify (Almeida and Kogut, 1999; Maskell and Malmberg, 1999). Hence, when switching jobs, workers diffuse tacit knowledge between plants. Hiring new managers and technicians thus infuses a plant with capabilities that would otherwise be hard to acquire, which may facilitate diversification. This is expected from an evolutionary perspective, as it enables plant-internal recombination of existing capabilities with the capabilities of a new employee. This would make activities possible that wouldn't be otherwise. New activities, in turn, are expected to reflect the plant's capabilities as well as the capabilities of the new employee. Hence, like Chapter 5, Chapter 6 explicitly focuses on the capabilities that underlie activities, and how those capabilities, diffused between plants through labor mobility, make new activities possible. The research question that Chapter 6 addresses is as follows:

What is the impact of new influx of capabilities into plants, through the recruitment of top managers and top technicians, on plant diversification?

To investigate this, the same Swedish matched employer-employee data as in Chapter 5 are used. A key empirical challenge in this setting is to identify a causal effect of new hires, as new hires might simply reflect a firm's strategy to diversify or some other omitted variable bias. To deal with this, an identification strategy partly based on geography is developed and applied, using the death or permanent emigration of an existing top manager or top technician in a plant on the one hand and a supply-shift instrument of skill availability in the region to predict what kind of human capital is hired as replacement on the other hand.

Chapter 7

Chapter 7, the final chapter, concludes and outlines the limitations of this PhD thesis and avenues for future research. Particularly, it elaborates on the role of institutions, measuring relatedness and capabilities and identifying causal effects of relatedness and knowledge transfer mechanisms on growth and change. It also presents policy implications.

2.

The impact of related variety on regional employment growth in Finland 1993–2006: high-tech versus medium/low-tech

Co-authors: Ron Boschma, Markku Sotarauta

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2.1 Introduction

In the context of the current economic crisis, the question of what kind of economic composition in regions is best for regional employment growth is more than ever prominent on the political and scientific agenda. Until recently, the key question was whether regions should be mainly specialized, or whether the economic composition of regions should be mainly diversified. Especially, the importance of regional diversity or Jacobs' externalities has been subject to much empirical work from the 1990s onwards (Glaeser et al., 1992; Van Oort, 2004), with mixed results so far. That is, studies have shown positive, negative or no impact of a diversified industrial mix in regions on their economic growth (see for an overview Beaudry and Schiffauerova, 2009). A possible reason for this is the crude way in which variety is often dealt with in the Glaeser-related literature (Iammarino and McCann, 2006).

In recent years, studies have challenged the view that a variety of sectors in a region as such is sufficient for local firms to learn and innovate from knowledge spillovers (Frenken et al., 2007; Boschma and Iammarino, 2009). Particularly, following Cohen and Levinthal (1990), it has been argued that learning from spillovers is unlikely to take place when there is no cognitive proximity between local firms. Recent literature has proposed that knowledge is more likely to spill over between sectors that are cognitively proximate (Nooteboom, 2000; Morone, 2006; Leahy and Neary, 2007). Frenken et al. (2007) have therefore introduced the notion of related variety, in order to underline that it is not regional variety per se that matters for urban and regional growth, but rather regional variety between sectors that are technologically related to each other. Recent studies in The Netherlands (Frenken et al., 2007), Italy (Boschma and Iammarino, 2009; Quatraro, 2010) and Spain (Boschma et al., 2012) have indeed confirmed that related variety tends to contribute positively to regional employment growth.

This study investigates the impact of related variety on regional growth in Finland between 1993 and 2006. Recent studies have argued that sectoral specificities might matter in this respect. We investigate whether related variety among high-tech sectors has affected regional growth in Finland in the period 1993-2006, during which time the Finnish economy changed into a high-tech economy. Some scholars (Heidenreich, 2009; Kirner et al., 2009; Santamaria et al., 2009) have argued that inter-industry knowledge spillovers and product innovations are especially relevant for high-tech sectors. The relationship between related variety and regional employment growth is examined by means of dynamic panel regressions using generalized method of moments (GMM) estimators, which allow us to take into account the possibility of reverse causality between related variety and regional growth over time. This makes the estimated effects dynamic in comparison to existing studies, which have been mainly cross-sectional.

The structure of this study is as follows. Section 2 elaborates on how agglomeration economies are linked to economic growth in regions, particularly related variety. Section 3 contains the empirical framework that describes the evolution of the Finnish economy from 1993 onwards in greater detail, and then elaborates on the data and the methods used.

Section 4 presents and discusses the results. A conclusion follows in the final section that also describes the challenges for future research on this topic.

2.2 Related variety and regional growth

Agglomeration economies refer to external economies of scale that arise from firms being concentrated close to one another in physical space, and from which firms can profit. In particular, agglomerations are an important source of increasing returns to knowledge (Rosenthal and Strange, 2004; Storper and Venables, 2004; Audretsch and Aldridge, 2008). Agglomeration economies are usually linked to three different sources: urbanisation economies, localisation economies and Jacobs' externalities.

The first source of agglomeration economies are urbanisation economies. These relate to external economies from which all co-located firms can benefit regardless of the industry they operate in. A dense environment in terms of population, universities, trade associations, research laboratories and so on, facilitates the creation and absorption of new knowledge, which in turn may lead to innovative performance (Harrison et al. 1996). As Lucas (1993) argues, productivity increases due to urbanization economies also result from increasing returns to scale to firms, for example due to the presence of larger labor markets in agglomerations. There are, however, also urbanisation diseconomies, such as higher factor costs, higher land prices and higher living costs. Furthermore, there may be negative externalities caused by pollution or congestion (Quigley, 1998). Thus, a dense environment provides advantages in terms of knowledge production and productivity increases, but may also be more costly to doing business than a scarcely occupied area.

The second source of agglomeration economies are localisation economies (Glaeser et al., 1992). They differ from urbanisation economies in that they refer to external economies that are available only to firms that operate within the same industry. In addition to labor pooling and the creation of specialized suppliers, localisation economies arise from knowledge spillovers that occur between firms that are cognitively similar (Henderson et al., 1995). An often cited example of the effects of these externalities is the uprising of the semiconductor industry in Silicon Valley, which was characterized by a process of self-reinforcing knowledge accumulation due to spatial proximity between specialized suppliers and customers, universities, venture capital firms and so on (Saxenian, 1994).

The third source of agglomeration economies are Jacobs' externalities. Named after the work of Jacobs (1969), these externalities originate from a variety of sectors in a region and are available to all local firms. The basic line of argument is that a regional economy characterized by a varied industrial mix spurs innovation because local firms are able to recombine knowledge stocks from different industries (Van Oort, 2004). Hence, the existence of regional variety itself is regarded as a source of knowledge spillovers. As such, Jacobs' externalities are likely to lead to regional employment growth because the recombination of knowledge from different industries fosters radical innovations that lead to the creation of new markets.

Studies on the effects of Jacobs' externalities on regional growth have produced mixed results so far. Some studies find either positive or negative effects, whereas others find no evidence for the presence of Jacobs' externalities (overviews are given in Beaudry and Schiffauerova, 2009; De Groot et al., 2009). Hence, there is ambiguity as to whether the presence of a diversity of industries is best for regional economic growth. In dealing with this, Frenken et al. (2007) and Boschma and Iammarino (2009) have recently argued that for Jacobs' externalities to occur in a region, the industries in the region have to be cognitively related to some extent. It is argued that learning between local firms is unlikely to take place when there is no cognitive proximity between them

Incorporating the notion of cognitive proximity into Jacobs' externalities, Frenken et al. (2007) make a distinction between related variety and unrelated variety. Related variety is defined as industries that share some complementary capabilities, while unrelated variety refers to sectors that do not. As expected, they find that it is related variety that mainly contributes to regional employment growth, whereas unrelated variety mainly acts as a local stabilizer, dampening regional unemployment growth. The latter result is expected because unrelated variety is unlikely to facilitate effective learning between firms due to the lack of cognitive proximity, and because it protects regions from negative sector-specific demand shocks. Similar findings of the impact of related and unrelated variety on regional growth have been found in the case of Italy (Boschma and Iammarino, 2009) and Spain (Boschma et al., 2011).

Hence, related variety as such seems to matter for growth, but to what extent do sector specificities matter in this respect? Henderson et al. (1995) already indicated that variety in general is more important for young and technologically advanced industries. Paci and Usai (2000) found that variety in general is more important for high-tech industries in urban regions. As for related variety, the results of the empirical study of Bishop and Gripaios (2010) suggest that the impact of related variety on growth differs for different sectors. Relatedly, Buerger and Cantner (2011) studied innovativeness in two science-based and two specialized supplier industries and found that for all four industries technological relatedness to other local industries is beneficial. Hence, it may be that the impact of related variety on growth depends on certain specificities of local sectors concerned, but empirical studies that have investigated this issue are yet scarce.

In this study we explicitly relate one sector specificity, namely the technological intensity of local sectors, to the impact of related variety on regional growth. Scholars (Heidenreich, 2009; Kirner et al., 2009; Santamaria et al., 2009) have argued that inter-industry knowledge spillovers and product innovations are especially relevant for high-tech sectors. We investigate regional growth in Finland between 1993 and 2006, a period during which the economy of Finland changed into a high-tech economy, with an increasing variety within the high-tech sector. Inspired by the approach taken by Frenken et al. (2007), we investigate by means of a dynamic panel regression whether the impact of related variety among high-tech sectors on regional growth in Finland is different from the impact of related variety among low-and-medium-tech sectors.

2.3 Methodology

2.3.1 Data

We employ annual data by industry at the regional level in Finland from 1993 to 2006. Regions are defined according to the NUTS-4 classification of the European Union, the borders of which approximate local labor market areas, which are commonly used in studies on local knowledge spillovers. The data have been obtained from Statistics Finland, which is the official statistics authority for the Finnish government. In the data, there have been changes in regional borders and industrial classifications over time, and the way in which those changes have been dealt with in this study is described in Appendix 2.A. There are 67 different regions in total.

The economy of Finland is very diversified at the regional level in terms of its industrial composition and technological intensity. Finland experienced a huge economic recession in the period 1990-1993, during which real GDP dropped by more than 10% and unemployment rose from about 4% to nearly 20% (Honkapohja and Koskela, 1999; Rouvinen and Ylä-Anttila, 2003). From 1993 onwards, the Finnish economy recovered dramatically: the average annual growth rate in GDP was 4,7% between 1993 and 2000 and the unemployment rate went down from nearly 20% in 1993 to around 9% in 2000. The economic boom was characterized by the upcoming of high-tech industries, especially those indulged in manufacturing electronic products related to telecommunication. Some firms, such as Nokia, played an important role in this respect (Ali-Yrkkö and Hermans, 2004). Whereas Finland had a large trade deficit in high-tech products in the early 1990s, it had a significant surplus in 2000, when exports of electronic equipment and other high-tech products accounted for more than 30% of the country's exports (Blomstrom et al., 2002). Hence, the data cover a time period (1993-2006) that contains an economic boom with a prominent presence of high-tech sectors.

2.3.2 Variables

Dependent variable

The dependent variable in this study is annual employment growth (EMPGROWTH) at the regional level (NUTS4) in Finland between 1993 and 2006. A limitation of employment growth is that it does not measure industry growth as accurately as growth in productivity, which relates more directly to learning from knowledge spillovers through related variety, but data on output is unfortunately unavailable at this spatial scale in Finland.

Independent variables

To measure the different indicators of variety at the regional level, regional establishment data are used which are classified according to the Finnish Standard Industrial Classification 1995 (SIC). This classification is derived from and corresponds with few exceptions to the

European Community NACE Rev. 1. Classification. Establishment data are available for all industries in every region at any digit level of the SIC classification.

Regarding the measurement of variety, we use an entropy measure on the regional establishment data. The advantage of using an entropy measure is that it can be decomposed at every sectoral digit level of the SIC classification. Hence, variety can be measured at several digit levels, and subsequently these different variety measures can enter a regression analysis without necessarily causing multicollinearity. We first measure variety in general that represents the degree of variety of establishments in a region as a whole. In turn, variety in general is decomposed into unrelated variety (UNRELVAR) and related variety (RELVAR), in a similar vein as in Frenken et al. (2007) and Boschma and Iammarino (2009). Subsequently, the contribution of this study is to further decompose related variety (RELVAR) into high-tech related variety (RELVARHTECH) and low-and-medium-tech related variety (RELVARLMTECH). First, let p_i be the five-digit SIC share of establishments, and S*g* the two-digit sector, then variety in general is measured as the sum of entropy at the five-digit level:

$$V = \sum_{g=1}^{G} P_i \log_2\left(\frac{1}{Pi}\right) \qquad \text{(Eq. 2.1)}$$

This measure thus represents regional variety in general, or Jacobs' externalities not further specified. The higher its value, the more diversified the industrial composition of a region is. To take into account the degree of cognitive proximity between sectors, and hence learning opportunities for industries, this measure is split into an unrelated and related part. First, one can derive the two-digit shares P_g by summing the five-digit shares p_i :

$$P_g = \sum_{i \in S_g} p_i \qquad \text{(Eq. 2.2)}$$

Then, unrelated variety (UNRELVAR) is measured by the entropy at the two-digit level:

$$UV = \sum_{g=1}^{G} P_g \log_2\left(\frac{1}{P_g}\right) \qquad \text{(Eq. 2.3)}$$

Hence, this variable UNRELVAR measures unrelated variety by means of variety at the two-digit level. We thus assume that sectors that belong to different two-digit classes are unrelated to one another. Hence, the higher the value of this variable, the more variety there is at the two-digit level, and thus the more a region is endowed with very different industries. It is expected that effective knowledge spillovers do not occur when the degree of UNRELVAR is high, because it is unlikely that sectors in different 2-digit classes can effectively learn from each other because they are not cognitively proximate.

We also measure related variety (RELVAR). Following Frenken et al. (2007), this is done by taking the weighted sum of entropy within each two-digit sector:

$$RV = \sum_{g=1}^{G} P_g H_g \qquad \text{(Eq. 2.4)}$$

where

$$H_g = \sum_{i \in S_g} \frac{p_i}{p_g} \log_2 \left(\frac{1}{p_i / p_g} \right) \qquad \text{(Eq. 2.5)}$$

Hence, this variable RELVAR measures the degree of variety within every two-digit class in a region, and sums that for all the two-digit classes in that region. We thus assume that sectors that belong to the same two-digit class are related to one another technologically, and hence we assume that they can effectively learn from one another through knowledge spillovers. And, the higher the degree of RELVAR is, the higher the number of technologically related industries in the region, the more innovation opportunities there are.

We further decompose related variety (RELVAR) into high-tech related variety (RELVARHTECH) and low-and-medium-tech related variety (RELVARLMTECH) to assess whether they have a different impact on regional employment growth. We use the SIC 1995 classification which separates low-and-medium-tech sectors from high-tech sectors according to their technological intensity, based on their R&D intensity (R&D expenditures over value added) and their share of tertiary educated persons employed. The latter also accounts for sectors that do not necessarily have a high R&D intensity, i.e. knowledge- and innovation-intensive sectors. This classification is commonly used to separate high-tech from low-and-medium-tech sectors in Finland (e.g. Simonen and McCann, 2008). Following this classification, high-tech related variety (RELVARHTECH) is measured in the same vein as related variety (RELVAR), but is applied only to establishments in high-tech sectors, all of which are listed in Table 2.1. Low-and-medium-tech related variety (RELVARLMTECH) measures related variety within all of the remaining industries. Because of the decomposable nature of the entropy measure that is used to measure both types of related varieties, they do not necessarily correlate with each other and hence can enter a regression at the same time. In Appendix 2.B we elaborate on this issue in greater detail and also describe how the empirical construction of both types of varieties differs from the traditional distinction between related and unrelated variety as in Frenken et al. (2007).

Table 2.1: High-technology industries based on SIC classification (1995)

Manufacture of pharmaceuticals, medicinal chemicals and botanical products	244
Manufacture of office machines and computers	30
Manufacture of radio, television, communications equipment and apparatus,	32
Manufacture of aircraft and spacecraft	353
Telecommunications	642
Computers and related activities	72
Research & Development	73
Architectural and engineering activities and related technical consultancy	742

2.3.3 Control variables

We include a number of control variables. First, regional population density (POPDENS) from 1993 to 2006 is used as a proxy for urbanisation economies. This variable represents the amount of economic activity in every region regardless of its industrial composition. Second, to measure the effect of human capital (HUMCAP) in a region, we take the percentage of the total population (1993-2006) with a university bachelor degree or higher. This way of measuring educational attainment is in line with most of the literature on human capital and regional growth. Third, Research & Development (R&D) expenditures (R&DEXP) are measured per capita from 1995 to 2006 (excluding 1996). This indicator plays a central role in endogenous growth models, and is also often used to measure the ability of regions to adapt to innovations produced elsewhere (Crescenzi and Rodríguez-Pose, 2008). These variables are some of the variables that are most often included in growth models, but we lack data on some other variables that are also known to influence growth (e.g. variables reflecting capital-labor ratios or competition). Hence, we are not able to estimate a conventional regional growth model with all of the 'usual suspects' included, but we are able to investigate whether the different variety measures have different regional employment effects. The control variables that we include are log transformed, and time dummies are included in the model.

2.3.4 Model specification

To determine the impact on regional employment growth, we adopt a dynamic panel approach using generalized method of moments (GMM) estimators developed by Arellano and Bond (1991) and Arellano and Bover (1995). The growth equation we wish to estimate has the following form:

$$y_{i,t} = \beta' X_{i,t} + \eta_i + \varepsilon_{i,t} \quad \text{(Eq. 2.6)}$$

where y denotes employment growth, t denotes 1-year intervals (from 1993 to 2006), I denotes the region, **X** denotes the set of explanatory variables, η denotes an unobserved region-specific effect of time-invariant determinants of growth and ε denotes the error term. The variety regressors may be endogenous because growth may also influence the variety in a region (e.g. growth may take place through a process of diversification into related industries as found in Neffke et al., 2011). Normally, one would deal with this issue by using external instruments that are correlated with $X_{i,t}$ and yet uncorrelated with $y_{i,t}$. Suitable external instruments, however, are unavailable in this case, which is a common problem in studies on regional growth (Henderson, 2003). Therefore, we use internal instruments based on lagged levels and lagged differences of $X_{i,t}$ generated with a GMM procedure.

Holtz-Eakin et al. (1988) and Arellano and Bond (1991) were the first to develop a GMM estimator with internal instruments for dynamic panel models such as Eq. (2.6). First, they take first differences to eliminate fixed effects:

$$y_{i,t} - y_{i,t-1} = \beta'(X_{i,t} - X_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) \qquad \text{(Eq. 2.7)}$$

Afterwards, they instrument potentially endogenous variables with their own levels, lagged twice or more. The estimator assumes that the error term, ε, is not serially correlated and that the explanatory variables, X, are weakly exogenous (uncorrelated with realizations of the error term in the future).

The estimator above, however, does not allow one to study cross-region differences between growth and the explanatory variables as this relationship is eliminated, which is problematic in the context of this study for two reasons. First, from a conceptual point of view we would be interested in studying this relationship as well. Second, lagged levels are weak instruments for the first-differenced equation, (Eq. 2.7), when the explanatory variables are persistent over time, which is likely the case with the different variety measures (as the sectoral composition of regions changes only slowly over time). This finite-sample bias may produce biased coefficients for first-differenced regression equations (Blundell and Bond 1998).

In dealing with this issue, Arellano and Bover (1995) developed a system-GMM estimator. It combines in a system the regression in levels, Eq. (2.6), with the regression in differences, Eq. (2.7), where levels are instrumented on lagged first differences (as above) and first differences are instrumented on lagged levels (assuming that past changes in y are uncorrelated with the current errors in levels or differences). Blundell and Bond (1998) show with Monte Carlo simulations that in small samples this estimator yields great improvements over the original Arellano and Bond estimator.

In this study we use the two-step variant of the system-GMM estimator and instrument the variety regressors with their lagged values. The two-step variant is asymptotically more efficient than the one-step variant in estimating coefficients but also tends to be severely downward biased when applied to the original Arellano-Bond-Blundell estimators, which we address by applying the finite-sample correction to the standard errors by Windmeijer (2005). We consider the different variety regressors (VARIETY, RELVAR, UNRELVAR, RELVARHTECH, RELVARLMTECH) as potentially endogenous and therefore instrument them with their lagged values. The other regressors are considered exogenous and hence are not instrumented as there is no direct theoretical concern to do so. Also, instrumenting them as well would overfit the model with instruments (a rule of thumb is not to exceed N with the number of instruments – derived from Arellano and Bond, 1998).

The extent to which the system-GMM estimator generates reliable parameters depends on whether the instruments used (in levels and differences) are valid instruments, which we assess as follows. First, we report for every model the results of the Hansen (1982) J test for overidentifying restrictions, which is robust for the two-step variant of the system-GMM estimator. Failure to reject its null hypothesis, that the instruments are exogenous as a group, supports the model. The only risk with this test is that it can be weakened by instrument proliferation (Bowsher, 2002), which we take into account by limiting the number of instruments to N as suggested by Roodman (2009a). We also report the results of separate difference-in-Hansen tests that assess the validity of the particular subsets of instruments (i.e. levels and differences, both with and without the other exogenous variables included) and have a similar null hypothesis as the Hansen J test.

Second, we assess the validity of the instruments by checking for autocorrelation in the error terms. This is done by applying the Arellano-Bond test to the residuals in differences (Arellano and Bond, 1991), which checks whether there is second-order serial correlation in the differenced error term (first-order serial correlation is present by construction because $\varepsilon_{i,t} - \varepsilon_{i,t-1}$ is related to $\varepsilon_{i,t-t} - \varepsilon_{i,t-2}$ because of the shared $\varepsilon_{i,t-t}$ term). If the null hypothesis of no autocorrelation is rejected, it means that the lags of the variety regressors are not exogenous and hence that they are unsuitable for use as instruments.

2.4 Results

As the correlations between some of the independent variables are high (see Table 2.2), we employed a conventional OLS regression on regional employment growth to calculate their variance inflation factor (VIF) score. We find that the different variety measures all score below 5, which suggests that multicollinearity does not substantially bias the results. The dynamic panel framework also renders multicollinearity less of a problem than it would be in a cross-sectional framework.

Figure 2.1 shows the development of the average related and unrelated variety at the regional level in Finland during the period 1993-2006. A trend is visible of increasing related variety at the regional level in Finland, although slowly evolving, which reminds us that the change of the industrial composition in regions is a slow and gradual process. By contrast, unrelated variety seems to be fairly stable over time. Related variety among high-tech sectors and related variety among low-and-medium-tech sectors both increase over time. Descriptive statistics (mean, standard deviation, minimum, maximum) of these different variety measures, together with descriptive statistics of the other variables, are shown in Table 2.3.

Table 2.4 shows the results of the system-GMM dynamic panel regression on regional employment growth. Three different models are estimated. Model 1 contains only the

Table 2.2: Correlation matrix of independent variables (pooled, cross-section 1993 – 2006)

Variables	RELVAR	UNREL VAR	RELVAR HTECH	RELVAR LMTECH	POPDENS (log)	R&Dexp (log)	HUMCAP (log)
RELVAR	1						
UNRELVAR	0.6564	1					
RELVARHTECH	0.8074	0.4834	1				
RELVERLMTECH	0.9981	0.6600	0.7693	1			
POPDENS (log)	0.5336	0.4494	0.6643	0.5081	1		
R&DPERCAP (log)	0.4948	0.3406	0.6974	0.4626	0.5949	1	
HUMCAP (log)	0.6565	0.4005	0.7334	0.6338	0.6463	0.7075	1

control variables. As is often found in the regional growth literature, the amount of human capital is positively related to regional employment growth, whereas population density has a negative impact. No significant effect of R&D expenditures is found.

Model 2 includes related variety (RELVAR) and unrelated variety (UNRELVAR). Both of them are instrumented with their lagged values. The model passes all the diagnostics tests for the validity of the instruments as none of the Hansen tests and Arellano Bond test are significant in Table 2.4, which means that the lagged values of related variety and unrelated variety are suitable instruments and that the model is not miss-specified. We find that related variety has no significant impact on regional growth. This is contrary to previous studies, but we have to remember that our model cannot replicate other studies due to missing control variables.

In Model 3 related variety is decomposed into high-tech related variety (RELVARHTECH) and low-and-medium-tech related variety (RELVARLMTECH). Both of them, together with unrelated variety (UNRELVAR), are instrumented with their lagged values. The model is not miss-specified as all the Hansen tests and the Arellano bond test are insignificant, which implies that the instruments used are valid instruments. We find that only related variety among high-tech sectors has a positive and significant impact on regional employment growth, whereas related variety among low-and-medium-tech sectors has a negative but insignificant impact. Although the impact of RELVARHTECH is significant at only 10%, its coefficient differs substantially from the coefficient of RELVAR in Model 2. Also, the coefficients of the other variables have hardly changed between Model 2 and Model 3, which implies that it is unlikely that the positive and significant coefficient of related variety among high-tech sectors is a result of interdependencies with the other variables, but instead is the result of separating it from low-and-medium-tech variety (RELVARLMTECH). This may explain why related variety as such has no impact on regional growth: after decomposing it into low-and-medium-tech related variety and high-tech related variety, it turns out that only the latter impacts positively on regional employment growth in Finland between 1993 and 2006.

Figure 2.1: Average related and unrelated variety at regional level in Finland, 1993-2006

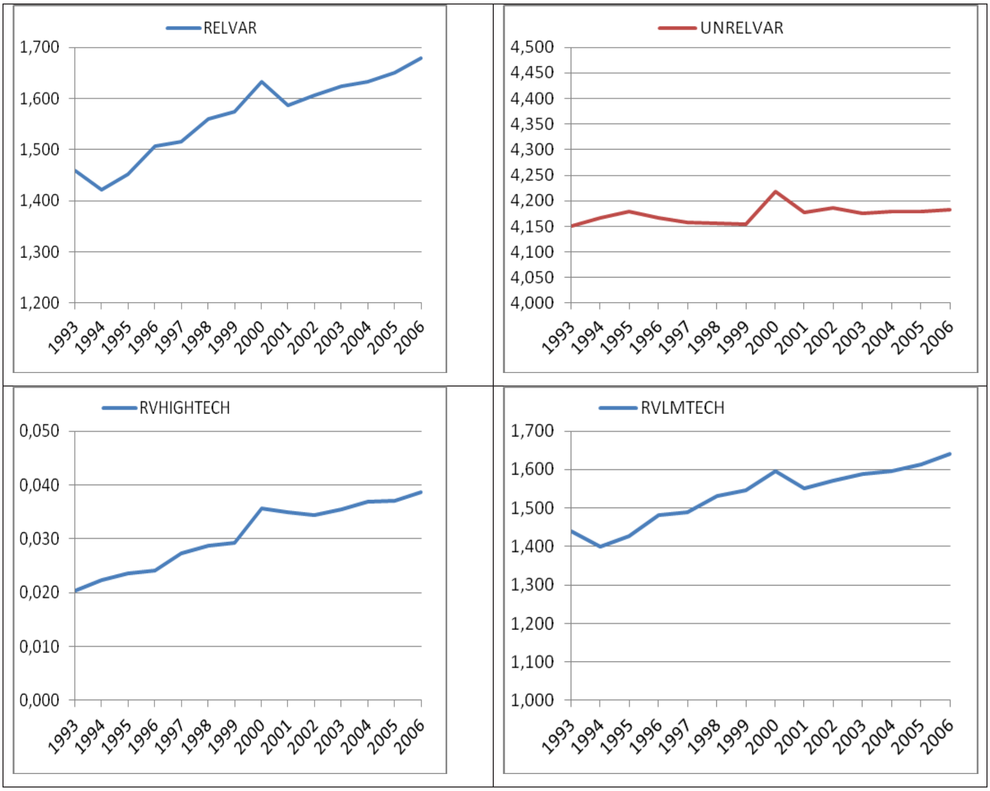


Table 2.3: Descriptive statistics of independent variables
(pooled, cross-section 1993 – 2006)

Variables	Mean	SD	Min	Max
RELVAR	1.564	0.461	0.334	2.979
UNRELVAR	4.173	0.347	2.935	4.773
RELVARHTECH	0.031	0.042	0.000	0.233
RELVERLMTECH	1.533	0.428	0.333	2.814
POPDENS*	42.438	117.221	0.686	918.066
R&DPERCAP*	334.910	481.645	4.088	3523.114
HUMCAP*	0.0570	0.276	0.016	0.185
*POPDENS, R&DPERCAP and HUMCAP enter the regression analysis log transformed				

Table 2.4: System-GMM dynamic panel regression on annual employment growth in Finnish regions, 1993-2006

	(1)	*(2)*	*(3)*
POPDENS (log)	-0.016)** (0.007)	-0.015** (0.007)	-0.020** (0.008)
R&DPERCAP (log)	-0.001 (0.008)	-.001 (0.008)	-0.011 (0.010)
HUMCAP (log)	0.032)*** (0.011)	0.030 ** (0.014)	0.026* (0.015)
UNRELVAR		-0.021 (0.021)	0.012 (0.029)
RELVAR		0.008 (0.011)	
RELVARHTECH			0.276* (0.162)
RELVARLMTECH			-0.019 (0.252)
Time dummies included?	Yes	Yes	Yes
Constant	0.142*** (0.042)	0.206** (0.087)	0.061 (0.119)
Hansen J-test (p value)		0.700	0.434
Arellano-Bond second order serial correlation test (p value)		0.249	0.240
Difference-in-Hansen test that GMM differenced instruments are exogenous (p value)		0.719	0.695
Difference-in-Hansen tests that system GMM instruments are exogenous (p value)		0.552	0.192
*Significant at 90%; **Significant at 95%; *** Significant at 99%; Standard errors in parentheses; Estimates of time dummies not reported to conserve space; Estimations done with xtabond2 package by Roodman (2009b); The maximum number of lags is restricted to 2 to keep the # of instruments below *N*; Data points with studentized residuals higher than 2,5 are identified as outliers and have been excluded (6 observations out of 881)			

A possible explanation may be the different innovation approaches in high-tech and low-and-medium-tech sectors. As high-tech sectors rely heavily on knowledge-related inputs and operate mainly at the technological frontier of their respective markets (Hirsch-Kreinsen et al., 2005; Santamaria et. al., 2009), their competitiveness depends mainly on their ability to produce radical innovations that lead to new products. Recent empirical research by Heidenreich (2009), using European Community Innovation Survey data and EU regional data, finds that the focus on product innovations is a key aspect that differs high-tech sectors from low-and-medium-tech sectors as the latter are instead more focused on process innovations. Santamaria et al. (2009) and Haukness and Knell (2009) also show that really new knowledge and technologies for new products are produced mainly in high-tech sectors. This may explain our finding that only related variety among high-tech sectors in a region enhances regional employment growth. As related variety in high-tech sectors facilitates learning through knowledge spillovers, it may enhance the product innovation capacities of local high-tech sectors, with new products and markets as a result, and therefore more regional employment growth.

The focus of low-and-medium-tech sectors on process innovations, instead, may explain our finding that related variety among low-and-medium-tech sectors has no significant impact on regional employment growth. According to Pavitt (1984), low-and-medium-tech sectors are mostly 'supplier dominated sectors' that are heavily dependent on purchased embodied technologies and products. Hence, innovation in low-and-medium-tech sectors is aimed at minimising costs through the improvement of production process technologies (see Kirner et al. 2009 for recent empirical evidence for this). In turn, process innovation concerns productivity improvements which often reduce the amount of labor necessary to produce a single unit of output (Edquist et al., 2001). As low-and-medium-tech related variety may facilitate learning with more process innovations as a result, it will have two opposite effects on employment growth. On the one hand, it may increase the competitiveness of local firms with an increase in the demand of labor as a result, on the other hand it may reduce the amount of labor needed due to labor productivity improvements. The balance between the two depends on various factors, such as demand elasticity (e.g. Combes et al., 2004), but this all makes it less likely that a positive effect of low-and-medium-tech related variety will be found.

2.5 Conclusion

The aim of this study is to investigate the impact of related variety on regional employment growth in Finland between 1993 and 2006. Using a dynamic panel framework, we find that related variety in general does not impact on regional growth. Instead, we find that only related variety among high-tech sectors has a positive impact on regional growth. Hence, the technological intensity of local sectors involved matters with respect to the impact of related variety on regional employment growth. We proposed that the different employment effects of related variety may be due to differences in innovation approaches of high-tech sectors and low-and-medium-tech sectors, but we have not investigated this issue in this study. Future research should shed more light on this matter.

There are a number of other issues that stem from this study that could be addressed in future research as well. The first issue is that Finland might be more of a unique case because its economy experienced a particularly rapid transformation towards high-tech sectors during the time period covered. During this period, particular firms, such as Nokia, have played an important role. Therefore, it may be that the findings of this study may differ from (regional) economies that did not experience such a transformation. Future studies on this topic in other countries could shed light on this issue.

The second issue relates to the measurement of technological relatedness between industries, which has been based on the Standard Industrial Classification (SIC). While this is to some extent defendable since this classification is based primarily on product relatedness, it does not necessarily reflect technological relatedness. More advanced relatedness measures have been developed recently, such as the skill-relatedness measure by Neffke and Henning (2013). They measure relatedness by the degree of labor flows between different industries with the idea that excessive labor flows between certain industries imply that those industries require similar skills and hence are related. Such a measure captures relatedness more directly and is therefore preferable, if such data are available of course, which was not the case for Finland.

The third issue relates to the region as the level of analysis. A drawback of focusing on regional growth is that it remains unknown where exactly growth takes place in the region. In the case of related variety, we assume knowledge spillovers to take place between technologically related industries but we do not observe any flows. These are shortcomings that plague almost all agglomeration economies studies, including this one. Future research could address these issues by focusing instead on the effects on growth rates of industries in regions (e.g. Bishop and Gripaios, 2010), and by measuring the effects of actual inter-sectoral knowledge flows at the regional level (as proxied by e.g. labor flows). Also, if one would replace the region by the firm as the unit of analysis, one could also avoid making stylized distinctions between high-tech and low-and-medium-tech at the sectoral level. Any type of sectoral analysis suffers from the fact that there is some ‘noise’ involved in the sense that all sectors contain, to some degree, different firms, in this case firms that could be classified as either low-and-medium-tech or high-tech (Kirner et al., 2009). Narrower sector definitions may reduce but do not solve this problem – instead, the best solution to this problem would be to draw upon firm data directly, which would enable one to estimate technological intensity more accurately.

When it comes to policy making, the outcomes of this study highlight two important issues. First, when developing regional growth strategies, it is of crucial importance for policy makers to take into account technological relatedness between local firms. Knowledge spillovers between local firms and hence learning only takes place when local firms are to some extent cognitively related. This means that stimulating variety as such, without taking into account relatedness between local firms is unlikely to increase the innovative performance of local firms. Second, policy makers have to consider what kind of regional growth they are aiming for. This is a particularly relevant question for the Finnish innovation and regional development policies that seem to rather be moving towards more focused policies instead of stimulation of cross-sectoral innovation (Edquist et al., 2009). At all events, if policy makers wish to boost regional employment growth, the findings of this study highlight that it is beneficial to stimulate related variety among high-tech firms and to make connections between high-tech industries that are technologically related.

Appendix 2.A: Regional border changes and Standard Industrial Classification (SIC) changes between 1993 and 2006

There have been changes in regional borders and the Standard Industrial Classification (SIC) between 1993 and 2006. Changes in regional borders concern the dissolution of some NUTS 4-areas. Those regions have been excluded from the analysis. A comparison of the data before and after the dissolution of these regions shows that regional changes in the data have been very minor.

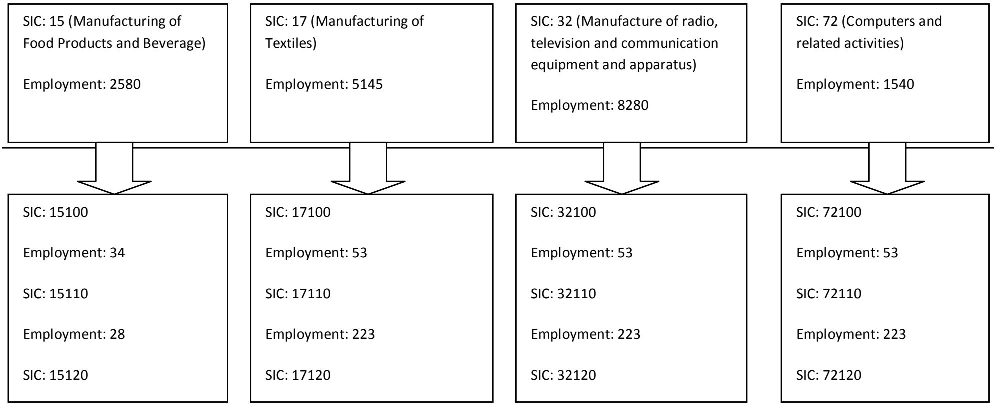
Regarding changes in the SIC classification, every single 5-digit change between 1993 and 2006 has been checked for and taken into account to make the data comparable over time. The changes concern exclusively the creation of new 5-digit sectors over time (23201 23209 27350 29400 33100 40121 40122 40131 40139 40140 40200 40310 40320 51360 51610 51620 51630 51641 51642 51643 51651 51652 51659 51660 51701 51709 52469 52474 52619 60240 63300 64203 65121 65129 72200 72400 74300 74409 74831 74832 74833 74839 74841 74842 74843 74849 85110 85129 85149 85317 85322 85329 93010 97000 99999). All the data have been recoded so that all the annual employment data from 1993 to 2006 follows the 1993 SIC classification.

Appendix 2.B: Measuring high-tech related variety, low-and-medium-tech related variety and unrelated variety.

Frenken et al. (2007) make a distinction between related and unrelated variety at the regional level using regional employment data. Their approach is depicted in Figure 2.2, using an example of a hypothetical region with employment in 4 sectors present. They use sectors that are classified according to the Standard Industrial Classification (SIC codes). Using entropy measures, unrelated variety is measured as the entropy at the 2-digit level, and related variety is measured as the weighted sum of entropy at the 5-digit level within every 2-digit sector. Hence, variety across 2-digit sectors represents unrelated variety and variety within 2 digit sectors represents related variety.

In this study we further decompose related variety into high-tech related variety and low-and-medium-tech related variety. This approach is depicted in Figure 2.3. In doing so, we draw upon the Finnish Standard Industrial Classification 1995 (SIC 1995) which is derived from and corresponds with few exceptions to the European Community NACE Rev. 1. classification. This classification separates high-tech sectors from low-and-medium-tech sectors on the basis of their R&D intensity (R&D expenditures over value added) and share of tertiary educated persons employed, the latter which also accounts for knowledge- and innovation-intensive sectors (which do not necessarily have a high R&D intensity). Consequently, we measure high-tech related variety as the weighted sum of five-digit entropy within all the 2-digit and 3-digit sectors that are classified as high-tech, which are the following: 244, 30, 32, 353, 642, 72, 73, 742 (see Table 2.1 in the main body of the chapter). Low-and-medium-tech related variety is measured as the weighted sum of entropy within all the remaining sectors (15, 17, and so on). Hence, the sum of low-and-medium-tech related variety and high-tech

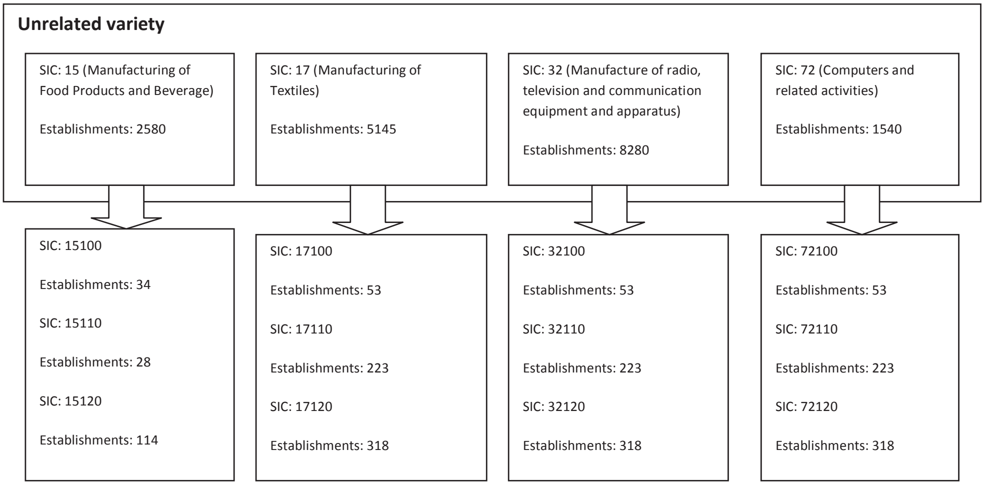
Figure 2.2: Related variety and unrelated variety as measured by Frenken et al. (2007)



related variety equals related variety (weighted sum of entropy within all 2-digit sectors) as depicted in Figure 2.3.

The entropy measure is decomposable within and across different levels of the SIC-classification, which implies that the different variety measures do not necessarily correlate with each other. Five-digit entropy is equal to the sum of the weighted sum of five-digit entropy within each of the 2- and 3-digit high-tech sectors (high-tech related variety) and the weighted sum of five-digit entropy within the remaining sectors (low-and-medium-tech related variety) and the two-digit entropy (unrelated variety). Hence, it would be possible for a region to have no unrelated variety, no low-and-medium-tech related variety, and much high-tech related variety. An equal amount of unrelated variety, low-and-medium-tech related variety and high-tech related variety would also be possible. Therefore, because the different variety measures do not necessarily correlate with each other, they can enter a regression simultaneously (a mathematical elaboration on the entropy measure and its decomposable nature can be found in, for example, Theil 1972).

Figure 2.3: High-tech related variety, low-and-medium-tech related variety, and unrelated variety as measured in this study



3.

Explaining the structure of inter-organizational networks using exponential random graph models

Co-author: Tom Broekel

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3.1 Introduction

To better understand how the composition of activities within a region affects development, it is important to understand how linkages between organizations and their activities come into being and how they change over time. The analysis of inter-organizational networks has received growing attention in recent years. As inter-organizational networks are seen as being important for innovation, there is a growing interest in the question as to what factors explain the structure of these networks (see, for example, the special issue by Organization Science that was devoted to this question - Ahuja et al., 2012). One of the key challenges identified is to investigate the relative importance of determinants at different levels of inter-organizational network structures. As a recent literature overview on this topic by Bergenholtz and Waldstrom (2011) shows, empirical studies have rarely done so.

Of those levels, most interest so far has been paid to the dyad level. For example, based on the different proximities set out by Boschma (2005), studies have investigated the impact of cognitive, organizational, social, institutional and geographical proximity between organizations on tie creation (e.g. Balland 2012, Broekel and Boschma, 2012). However, factors at the node level (e.g. size of an organization) and, more recently, factors at the structural network level have been highlighted to impact the structure of networks as well (Glückler, 2007; Boschma and Frenken, 2010; Phelps et al., 2012). For example, the triadic closure hypothesis predicts that partners of organizations are more likely to become partners as well, which implies that new tie creation depends on the existing structure of a network. A key methodological challenge in this respect is to separate the effect of dyad level factors from the effect of factors at the node level and structural network level.

To do so, factors at all three levels need to be included simultaneously in a model on network formation. This is possible when longitudinal network data are available, for example with a stochastic actor-based network approach (Burk et al., 2007; Snijders et al., 2010). However, longitudinal data for inter-organizational networks are, unfortunately, often unavailable, especially for informal networks. Hence, the question is how to investigate which factors explain the structure of an inter-organizational network that is observed at only one point in time.

In this study, we propose that exponential random graph models (ERG-models) provide an answer to this question. These models are a new set of network analysis techniques that have been developed in mathematical sociology (Snijders et al., 2006; Robins et al., 2006, 2007; Wang et al., 2012) and are increasingly used by scholars across scientific disciplines, for example in biosciences (Saul and Filkov, 2007), life sciences (Fowler et al., 2009) and political science (Cranmer and Desmarais, 2011). The reason for this is that ERG-models only require cross-sectional network data but allow one to simultaneously estimate the effect of factors at the node, dyad, and structural network level. For this reason, we believe, as we set out in this study, that they are also useful to analyze the determinants of the structure of inter-organizational networks.

The study is structured as follows. The second section gives an overview of factors at the node, dyad and structural network level that may have an impact on the structure of inter-organizational networks. The third section elaborates on the ERG-model. The fourth section, introduces an inter-organizational network, namely the knowledge sharing network of Dutch aviation organizations in 2008, to which an ERG-model is applied to explain its structure. The fifth section reports the results, followed by a conclusion in the sixth section.

3.2 Determinants of inter–organizational network structures

Central to understanding the formation of an inter-organizational network and its structure is the interplay between tie creation between actors and the existing structure of a network. Glückler (2007, p. 622) argues that: "A theory of network evolution, thus, looks at the changes that every new tie produces in the existing structure and, conversely, at the impact that the structure imposes on the formation of the next tie. Note that the unit of analysis is always dyadic tie formation, whereas the object of knowledge is network structure". Recent theoretical accounts on inter-organizational network formation, coming from and drawing on different strands of literature, by Ter Wal and Boschma (2009), Boschma and Frenken (2010), Ahuja et al. (2012) and Phelps et al. (2012), have identified several factors that may impact tie creation and hence determine the structure of inter-organizational networks. Those are factors at the (1) dyad (pair) level, (2) the node (organizational) level, and (3) structural network level. We elaborate below on the factors that are most often identified at each of these three levels.

First, the dyad level refers to relational properties: the characteristics of a relationship between two actors in a network. A key idea in sociology is that actors are more likely to be tied when they have similar attributes, which is known as a homophily effect (McPherson et al., 2001). Related to inter-organizational networks, this idea corresponds most closely to Boschma and Frenken (2010), who argue that tie creation between organizations is more likely when they are geographically, cognitively, socially, institutionally, or organizationally proximate. Geographical proximity may matter because it facilitates frequent face-to-face contacts between organizations' personnel, which may ease the creation and maintenance of ties between organizations (Maggioni et al., 2007; Ter Wal, 2011; Balland 2012). Cognitive proximity may matter because organizations are more likely to learn from one another when their knowledge assets are related (Cohen and Levinthal, 1990; Nooteboom, 2000). Hence, organizations may prefer to tie to organizations that are technologically related as they are then better able to understand one another (Knoben and Oerlemans, 2006). Social proximity refers to already existing social relations between organizations. It may matter for tie creation as it eases contact between organizations (Maskell and Malmberg, 1999; Sobrero and Roberts, 2001; Tiwana, 2008). Individuals at different organizations who know one another at a personal level may be more likely to collaborate, for example in asking one another for technological advice (Breschi and Lissoni, 2009). A key factor in this respect is trust, which facilitates interaction between organizations (Maskell and Malmberg, 1999; Sobrero and Roberts, 2001; Tiwana, 2008). For example, Agrawal et al. (2006) find that firms are more often tied when their employees have worked for the same organization before and hence already know one another personally. Institutional proximity refers to the extent to which organizations have related routines and incentive mechanisms (Metcalfe, 1995). If organizations have little institutional proximity they may have a lower chance of being tied (Ponds et al., 2007; Balland, 2012). For example, such may be the case for firms and universities because of their different incentives regarding knowledge creation and exchange (keeping new knowledge secret versus publishing new knowledge). Organizational proximity is defined by Boschma (2005, p. 65) as “the extent to which relations are shared in an organizational arrangement, either within or between organizations”. Strategic interdependence between organizations exists, for example, in joint ventures. Within organizations, establishments of different organizations may be subsidiaries of one parent organization. Balland (2012) found that if organizations are members of the same corporate group, they are more likely to be tied. The five proximity dimensions identified above are not mutually exclusive, they may overlap and reinforce one another. For example, geographical proximity may foster social proximity as it faciliates face-to-face contact on a regular basis.

Second, the node level refers to properties of network actors themselves. For example, size may matter in the sense that large organizations are more likely to establish ties because they occupy a more prominent position in an industry and have more resources to maintain ties than small organizations. Boschma and Ter Wal (2007) find that in the knowledge network of footwear producers in Barletta, larger organizations are more centrally located. Another example is the knowledge base of an organization. Giuliani and Bell (2005) find that organizations with a more advanced knowledge base are more often approached by other organizations to exchange knowledge. This may be because such organizations are more often perceived by others as ‘technological leaders’. Other properties at the node level may also matter for tie creation between organizations, such as the age of an organization, the industry in which it operates, the growth it has experienced in recent years, and so on.

Third, the structural network level refers to properties of the entire network. Regarding inter-organizational networks, tie creation at this level may specifically be driven by two factors: triadic closure and multi-connectivity (Glückler, 2007). Triadic closure implies that partners of organizations are likely to become partners as well. As a result, the network consists of many triangles, dense cliques of strongly interconnected organizations (Ter Wal, 2011). Such cliques are generally seen as a sign of social capital (Coleman, 1988) and as such enhance trust and willingness among actors to invest in mutual goals such as knowledge sharing (Beamish and Lupton, 2009). Multi-connectivity refers to the tendency of organizations to connect to others in multiple ways in order to decrease the dependency on a single link or channel. This implies that multiple paths are formed amongst organizations to achieve multiple reachability. Evidence for this is found by Powell et al. (2005), who study new tie creation between US biotech firms in terms of inter-firm alliances.

To estimate the relative importance of the factors at all three levels above to explain new tie creation and hence the structure of a network, they need to be simultaneously incorporated in a model. With longitudinal data, this is possible with a stochastic actor-based network approach that models the change of a network from one state (point in time) to another as part of an iterative Markov chain process (see for technical details: Snijders et al., 2010). Models based on this approach have been applied to inter-organizational networks very recently (Ter Wal, 2011; Balland, 2012).

A requirement of these models, however, are longitudinal network data, which are, unfortunately, often unavailable for inter-organizational networks. This is especially true when the network concerns informal ties between organizations (e.g. social contacts, asking for advice etc.). Such ties can only be observed by interviewing organizations' employees, who only have a limited memory of the past. If some links are unobserved (missing data), the structure of the observed network could be very different from the real-world network. Proper network analysis requires data that cover all or nearly all actors of the population, which, moreover, in case of longitudinal studies should also be complete for all time periods investigated.

As this is often a problem for inter-organizational networks, one is required to use models for cross-sectional network data. So far a number of those models have been applied in this respect, particularly binary logit models (e.g. Kaufman et al., 2003), gravity models (e.g. Hoekman et al., 2009) and multiple regression quadratic assignment procedure models (MRQAP models: e.g. Cantner and Graf, 2006; Broekel and Boschma, 2012). A major limitation of these models, however, is that they can account for factors at the dyad level only. As a result, the effect of dyad-level factors may be overestimated. An example in this respect are three organizations that are fully connected (triangle). One may see the three links as being fully independent. However, it can also be the case that in the network as a whole there is a general tendency to form triangles. Accordingly, not the dyadic relations between the three organizations are the main driver behind the three links but the networks' tendency to form triangles. The latter corresponds to the above mentioned 'triadic closure' hypothesis.

The main advantage of exponential random graph models is that they are able to simultaneously incorporate factors at the dyad level, node level and structural network level. We know of only one empirical study so far that has applied those models in inter-organizational network research, namely Lomi and Palloti (2012), who investigate collaboration in the form of patient sharing between hospitals.

3.3 Exponential random graph models

Exponential random graph models (ERG-models) are stochastic models that approach new tie creation as a time-continuous process. An observed network at one point in time is regarded as one particular realization out of a set of multiple hypothetical networks with similar properties. The aim of ERG-models is to identify the factors that maximize the probability of the emergence of a network with the same properties as the structure of the observed network.

The general form of ERG-models is defined as follows (Robins et al., 2007):

$$\Pr(Y = y) = \left(\frac{1}{\kappa}\right)\exp\left\{\sum{}_{\mathrm{A}}\eta_{\mathrm{A}}\; g_{\mathrm{A}}(y)\right\} \qquad \text{(Eq. 3 1)}$$

where Pr(Y=y) is the probability that the network (Y) generated by an exponential random graph is identical to the observed network (y), κ is a normalizing constant to ensure that the equation is a proper probability distribution (summing up to 1), η_{A} is the parameter corresponding to network configuration A, and g_{A}(y) represents the network statistic. Network configurations can be factors at the node level, dyad level and structural network level. Their corresponding network statistic obtains a value of 1 if a configuration is observed in the network y and 0 if not.

Estimation of the parameters is done with maximum pseudo likelihood or a Markov Chain Monte Carlo Maximum Likelihood Estimation procedure. The latter has been developed most recently and is regarded as the preferred procedure as it is often most accurate (Snijders, 2002; Van Duin et al., 2009). It is based on the generation of a distribution of random graphs by stochastic simulation from a starting set of parameter values, and subsequent refinement of those parameter values by comparing the obtained random graphs against the observed graph. This process is repeated until the parameter estimates stabilize. If they do not, the model might fail to converge and hence becomes unstable (see for technical details, Handcock 2003, and Hunter et al. 2008). This procedure is implemented in computer software such as SIENA, pnet or statnet (see Robins et al., 2007; Goodreau et al., 2008; Ripley et al., 2012).

Checking whether the parameters predict the observed network well (the model's goodness of fit) is done by comparing the structure of the simulated networks to the structure of the observed network. According to Hunter et al. (2008), the comparison concerns the degree distribution, the distribution of edgewise shared partners (the number of links in which two organizations have exactly k partners in common, for each value of k), and the geodesic distribution (the number of pairs for which the shortest path between them is of length k, for each value of k). The more the distributions of the simulated networks are in line with those of the observed network, the more accurate the parameters of the ERG-model are.

3.4 Empirical application: Investigating the structure of the knowledge network in the Dutch aviation industry

As an illustrative example of their usefulness, we apply an ERG-model to investigate the structure of the Dutch aviation knowledge network as observed in 2008, using data from Broekel and Boschma (2012). Whereas they have only investigated factors at the dyad level, primarily different types of proximities, the ERG-model allows us to include factors at the node and structural network level as well, both of which may provide additional or alternative explanations for the structure of the network.

3.4.1 Data

The data concern network data on technological knowledge sharing between Dutch aviation organizations in 2008. These data have been gathered by semi-structured interviews held with members of the Netherlands Aerospace Group (NAG), whose members account for about 95% of total turnover generated by Dutch aviation organizations (NAG, 2008). Interviews were held with 59 profit and non-profit organizations out of a population of 64 organizations, hence the response rate is 93%. The organizations were asked to indicate with which other aviation organizations they exchanged technological knowledge. The links in the network represent the knowledge ties that follow from this. Following Boschma and Ter Wal (2007) and Broekel and Boschma (2012), we approach knowledge exchange as being a mutual process between two organizations as the exchange of information goes both ways (regardless of whether or not both organizations actually benefit from the specific knowledge that is exchanged). Hence, if i named j as a relevant contact, we also assume that i is a relevant contact of j. As such, the network is symmetrized: all links between organizations are undirected. Figure 3.1 shows the knowledge network of the Dutch aviation industry in 2008 and Table 3.1 shows some descriptive statistics of it.

3.4.2 Variables

Dyad level variables

At the dyad level we follow Broekel and Boschma (2012) and analyze the impact of social, institutional, geographical and cognitive proximity on the structure of the network. We do not measure organizational proximity because we lack data on this dimension.

Social proximity (SOCPROX) amounts to a value of 1 if members of the top management of two organizations were former employees of Fokker B.V., and 0 if not. The motivation for this is that Fokker B.V. has been the dominant firm in the Dutch aviation industry until 1996 when it went bankrupt. Since then, many of its employees have been hired by other organizations or started their own business. Having a shared past in Fokker may increase the chance of being tied as 'old boys' networks might still be in place, which may provide exclusive knowledge sharing opportunities.

Institutional proximity (INSTPROX) is measured by differentiating between profit organizations (firms) and non-profit organizations (universities, research institutes, associations and trade organizations). Being a similar kind of organization may increase the chance of being tied. Most non-profit organizations are highly connected in the technological knowledge network (Figure 3.1). The variable's value is 1 if both organizations share the same institutional background and 0 otherwise.

Geographical proximity (GEODIST) is measured as the logarithm of the physical distance between two organizations (see for a discussion of this variable related to tie creation a recent special issue in Social Networks – Adams et al. 2012). The chance of being tied is expected to decrease with geographical distance.

Cognitive proximity (COGPROX) has a value of 1 if both organizations are active in

Figure 3.1: Knowledge network of Dutch aviation organizations, 2008

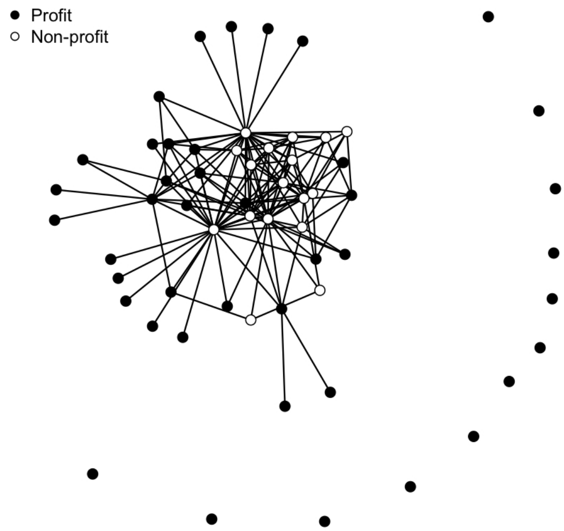


Table 3.1: Network descriptives, knowledge network of Dutch aviation organizations, 2008

Attributes	Value
Nodes	59
Links	146
Density	0.085
Max. Component	47
Isolates	12
Degree Centralization	0.411
Between. Centralization	0.213
Mean degree	9.890
Average distance in main component	2.122

at least one identical technology, and 0 if not. We rely on the technology classes that are assigned by the Netherlands Aerospace Group (NAG) and the organizations' webpage. The technological fields and corresponding number of organizations are listed in Table 3.2.

We also include two control variables at the dyad level. Aviation similarity (AVIASIM) has a value of 1 if two organizations are dedicated towards aviation and 0 if not. Because of a shared focus, organizations may be more likely to be tied. For firms, aviation dedication is measured by the share of their turnover attributed to aviation, which should be above the average of all firms involved. In case of other organizations, we define them to be aviation-dedicated if they indicated themselves that it is their primary focus. Organizations may also be characterized by varying openness towards external knowledge. Two organizations that consider external knowledge as highly important are more likely to link than two

Table 3.2: Netherlands Aerospace Group (NAG) technological fields

Technological field according to NAG	Number of firms
Airframe subsystems & components	17
Interiors	10
Propulsion & engine components	15
Auxiliary systems	5
Avionics, simulation & control	12
Education & training	13
General services	3
Engineering & R&D	31
Space subsystems & components	15
Maintenance & overhaul	11
Spare parts	10
Special materials.	10
Consultancy	5

organizations that primarily rely on firm-internal knowledge. We therefore create a dyadic variable that captures organizations' external openness (EXTERNALSIM). It has a value of 1 if the relative importance that organizations i and j attribute to external knowledge is above average and a value of 0 if not. Information on this was obtained by asking organizations to indicate the relative importance of knowledge acquired inside and outside the organization.

Node level variables

At the node level we include two variables. First, we define SIZE by the organizations' number of employees. Larger firms may be more likely to be tied to other organizations. Second, as private and profit organizations may show distinct cooperative behavior, a variable is created that represents non-profit organizations (NON-PROFIT).

Structural network level variables

We include five variables at the structural network level. Triadic closure is captured by the geometrically weighted edgewise shared partner statistic (GWESP-statistic: Snijders et al., 2006; Hunter et al., 2008). It measures the number of triangles in the network while taking into account the number of ties that are involved in multiple triangles (multimodality) and hence may have the same neighbors in multiple triangles (see for details: Hunter et al., 2008). If a positive parameter is found for this statistic, there is a tendency towards triadic closure in the network. Multi-connectivity (MULTICON) is captured by the alternating independent two-path statistic as defined by Snijders et al. (2006). This statistic measures how many partners every pair of organizations shares. Because it does so for pairs of organizations that are not linked amongst themselves, it is a lower order parameter to the GWESP-statistic. If this statistic's parameter is positive, there is a tendency towards creating multiple paths among organizations in the network. Finally, we include three control variables at the structural network level: EDGES equals the number of links in the network, ISOLATES accounts for the share of isolates in the original network, and GWDEGREE is the sum of each degree's count, weighted with a decay parameter. The latter variable helps modelling the observed network's degree distribution.

3.4.3 Results

To find the best fitting ERG-model, one has to run multiple alternative models until the model is stable and converges (when the Markov Chain Monte Carlo approach is used, the parameter traces should be horizontal) and provides the best goodness-of-fit statistics (matching degree, edgewise shared partners and geodesic distributions) given the empirical data (observed network). An example of a non-satisfying model is presented in Table 3.3. Following most other studies, it represents an ERG-model with only the dyad-level variables included. As this ERG-model is equivalent to a logistic regression, the EDGES parameter is included as well, which in this case acts as an intercept term. In addition, the model can be fitted using a maximum pseudo likelihood estimation procedure. Two parameters are significant, EDGES and GEOPROX. The latter's negative coefficient indicates that geographical distance is negatively related to the likelihood of tie creation, which is in line with the theoretical predictions and with the results obtained for the same network by Broekel and Boschma (2012). However, the goodness of fit statistics of this model (Figure 3.2 of the Appendix 3.A) show that the obtained coefficients are unreliable as the predicted degree distributions, edgewise shared partners distributions and geodesic distributions (boxplots and dashed lines) do not match the distributions of the observed network (solid line). Therefore, including only dyadic factors does not yield a fitting model for this network.

The best-fitting model we found for the knowledge network of the Dutch aviation industry is presented in Table 3.4. Included now are factors at the node, dyad and structural network level, exemplifying the main advantage of ERG-models. The model is now stable (no sign of degeneracy) and converges as indicated by the horizontal parameter traces (Figures 3.3a-3.3d in the Appendix 3.A). The model also shows goodness-of-fit statistics that are much more accurate (matching degree, edgewise shared partners and geodesic distributions – Figure 3.4 in the Appendix 3.A) than in the dyadic model. Moreover, the AIC (Akaike information criterion) and the BIC (Bayesian information criterion) are smaller in this model. These two criteria are commonly used to assess the goodness-of-fit of models estimated by means of maximum likelihood estimations. They also consider the number of explanatory factors used in the estimation. Small AIC and BIC values indicate a better model fit. The only factor that is not included in the model is the multi-connectivity variable (MULTICON), which always yields unstable models.

The results of the ERG-model in Table 3.4 can be interpreted as follows. At the dyad level, four factors are significant. EXTERNALSIM and AVIASIM have significant positive coefficients, which implies that organizations that value external knowledge high and those with stronger engagements in the industry are more likely to be tied. Out of the 4 proximity types, we find that only 2 of them impact tie creation. The coefficient for institutional proximity (INSTPROX) is

Table 3.3: Results ERG-model with only dyad level variables

	(1)
EXTERNALSIM	0.218 (0.211)
AEROSIM	-0.068 (0.219)
SOCPROX	-0.579 (0.425)
GEODIST	-0.248*** (0.058)
INSTPROX	0.116 (0.189)
COGPROX	0.226 (0.180)
EDGES	-1.579*** (0.278)
AIC BIC	991.14 1029.2

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Standard errors in parentheses

Table 3.4: Results ERG-model with dyad level + node level and structural network level variables

	(1)
NON-PROFIT	169.116*** (0.223)
SIZE	0.15*** (0.046)
EXTERNALSIM	0.449** (0.217)
AEROSIM	0.834*** (0.237)
SOCPROX	0.533 (0.483)
COGPROX	0.031 (0.200)
INSTPROX	0.626** (0.245)
GEODIST	-0.226*** (0.071)
GWESP(0.1 fix)	0.689*** (0.267)
GWDEGREE (0.1)	-0.868 (0.559)
EDGES	-554.613*** (0.614)
AIC BIC	715.22 775.11

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Standard errors in parentheses positive and significant: organizations with a similar institutional background are more likely to be tied. (GEOPROX) has a negative significant coefficient, which implies that geographical distance hampers tie creation. All of the findings above are in line with Broekel and Boschma (2012). However, social proximity (SOCPROX) and cognitive proximity (COGPROX) now turn out to be insignificant. This differs from the findings of Broekel and Boschma (2012), which is caused by the simultaneous inclusion of the factors at the node and structural network level variables.

At the node level, NON-PROFIT and SIZE are positive and significant. Hence, non-profit organizations are more likely to be tied to other organizations than profit organizations. This is in line with the visual inspection of the network in Figure 3.1, which shows that non-profit organizations generally have more links. Larger organizations are also more likely to be tied to other organizations.

At the structural network level, triadic closure is found be a driver of tie creation. The GWESP-statistic is positive and significant, confirming the fact that a relatively large number of triangles exists in the network (Figure 3.1). Hence, partners of organizations are more likely to become partners as well. As in the dyad-factors-only model, EDGES is negative and significant. In summary, regarding the overall model, in comparison to Broekel and Boschma (2012) we find that the inclusion of factors at the node and structural network level renders the effect of the factors at the dyad level (proximities) on tie creation less important. This highlights the importance of simultaneous estimation of the impact of the factors at all three levels, which is the main advantage of ERG-models.

3.5 Conclusion

The aim of this study was to introduce exponential random graph models (ERG-models) as useful models to explain the structure of inter-organizational networks that are observable at only one point in time. In recent literature, explanatory factors have been proposed at the node level, dyad level and structural network level. The main advantage of ERG-models is their ability to simultaneously include factors at all of these levels, which is why they have grown increasingly popular across scientific disciplines in recent years.

As an illustrative example of their usefulness in inter-organizational network research, we applied an ERG-model to explain the structure of the Dutch aviation knowledge network as observed in 2008. This is an example of an inter-organizational network of both formal and informal ties, of which it is almost unfeasible to collect complete network data at more than one point in time. We found that factors at all levels matter for the structure of the network, which is something we would not have been able to find with other models that are able to deal with cross-sectional network data. Relatedness (cognitive proximity) is not found to affect tie formation, whereas triadic closure is found to have a positive effect. Hence, because of their ability to incorporate factors at the node, dyad and structural network level of tie creation to model the structure of a network that is observed at only one point in time, we believe ERG-models have promising potential for future studies on inter-organizational network, particularly in evolutionary studies in economic geography.

Appendix 3.A: Goodness of fit graphs

Figure 3.2: Goodness of fit ERG-model with only dyad level variables

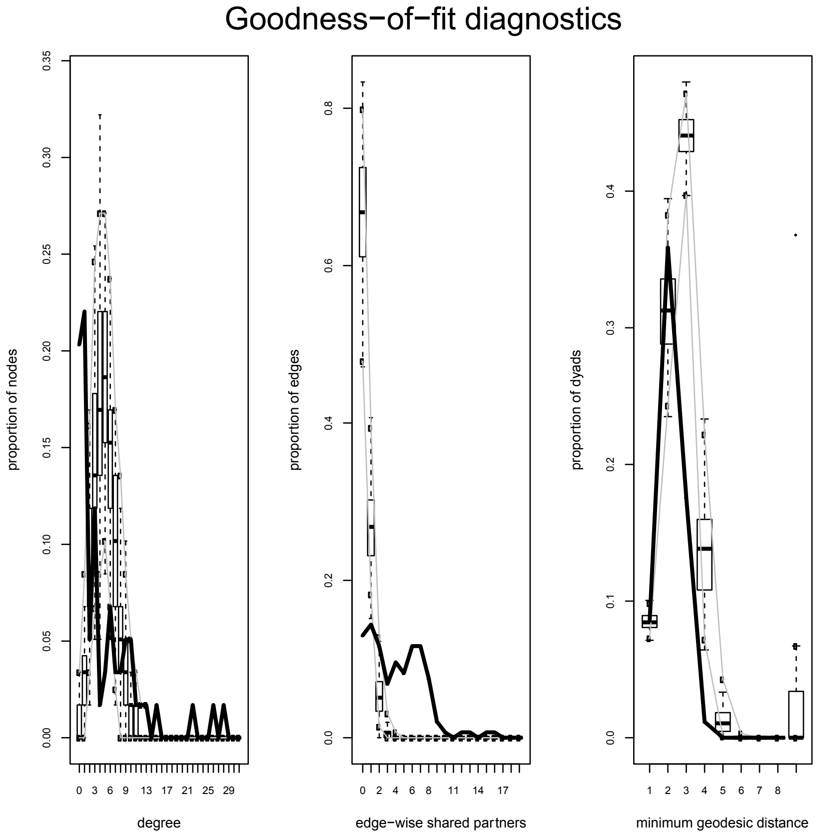


Figure 3.3a: Goodness of fit ERG-model with dyad level + node level and structural network level variables

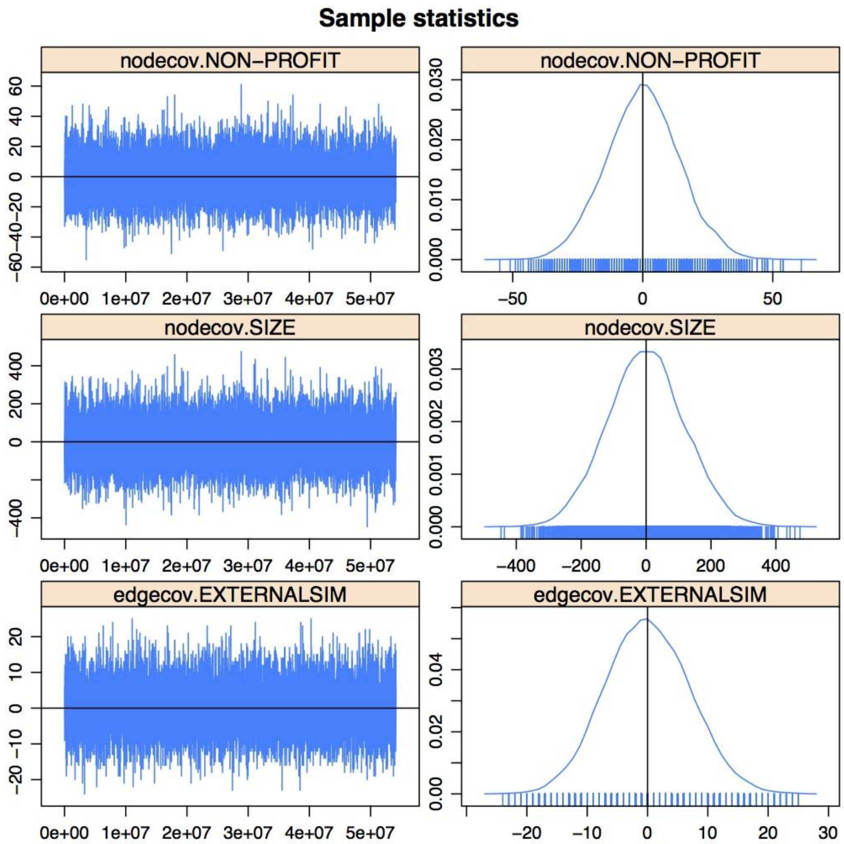


Figure 3.3b: Goodness of fit ERG-model with dyad level + node level and structural network level variables

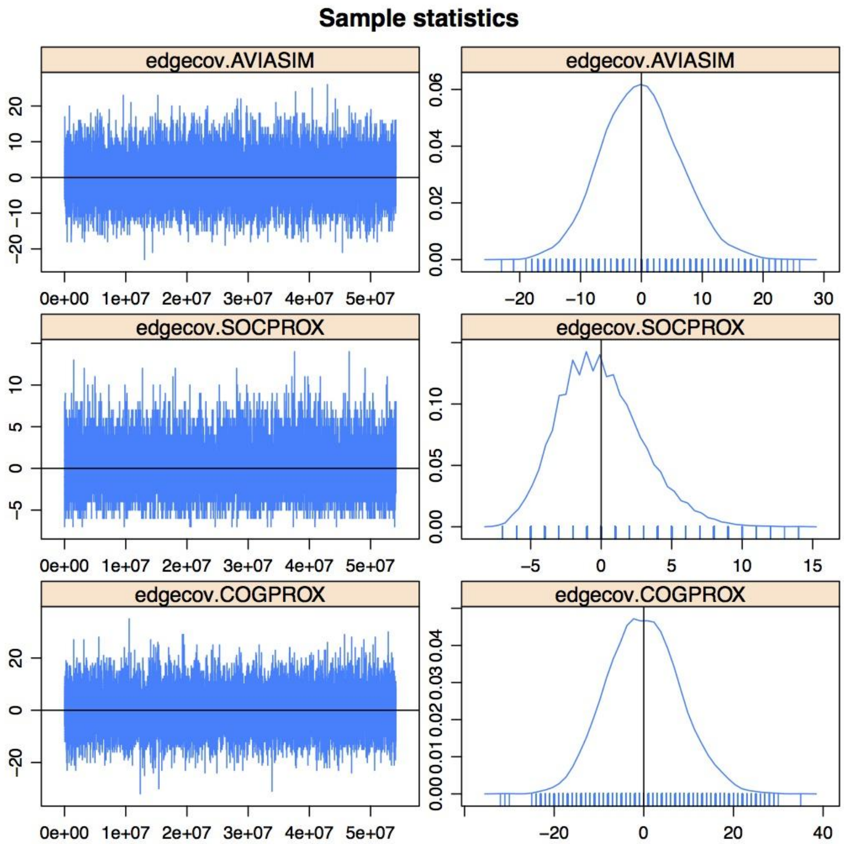


Figure 3.3c: Goodness of fit ERG-model with dyad level + node level and structural network level variables

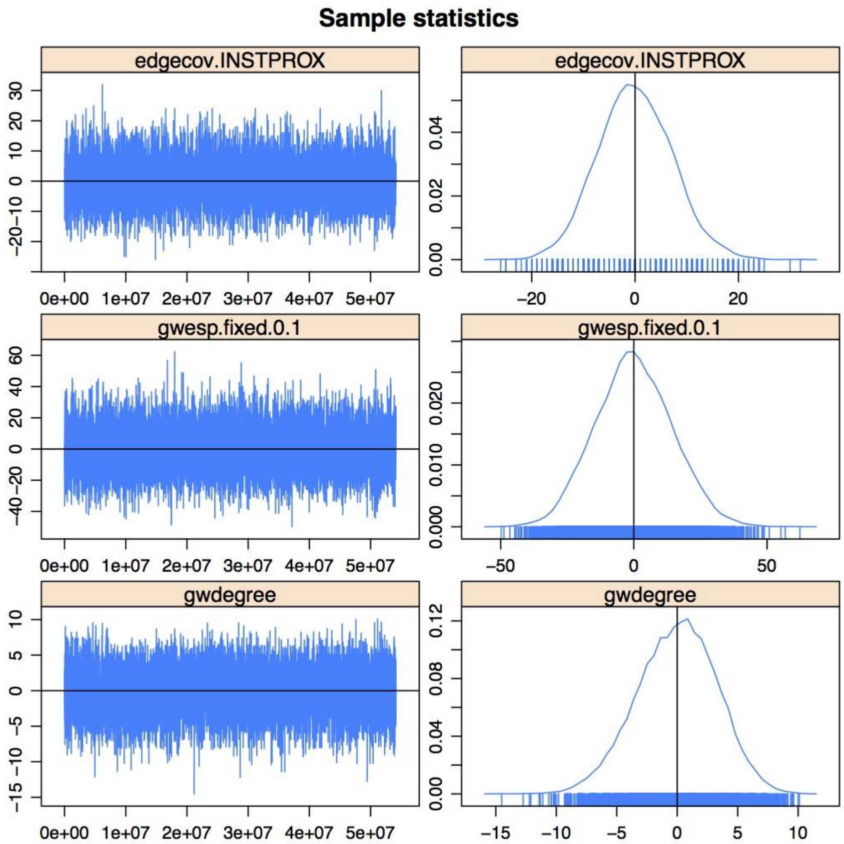


Figure 3.3d: Goodness of fit ERG-model with dyad level + node level and structural network level variables

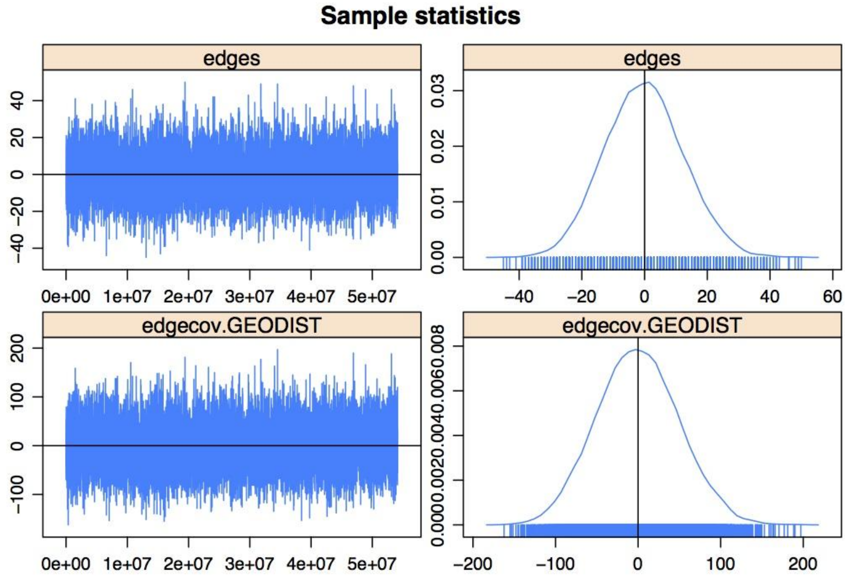
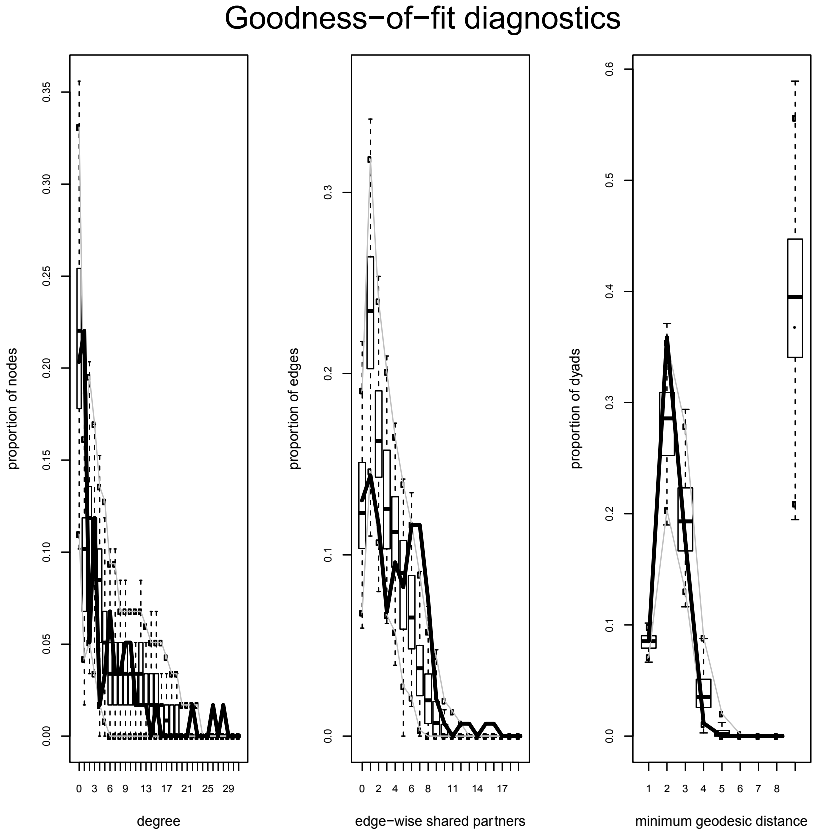


Figure 3.4: Goodness of fit ERG-model with dyad level + node level and structural network level variables



4.

Merger and Acquisition Activity as Driver of Spatial Clustering: The Spatial Evolution of the Dutch Banking Industry, 1850–1993

Co-author: Ron Boschma

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4.1 Introduction

Economic geographers have long been preoccupied with the question of how to explain the spatial clustering of an industry. Following Marshall (1890), they have referred to the importance of localization economies, due to a pool of specialized labor, the presence of specialized input suppliers, and access to knowledge about the secrets of the respective trade. This Marshallian view has been challenged recently. Klepper (2007), among others, has claimed that the spatial concentration of an industry emerges through a self-reinforcing spin-off process in which incumbent firms give birth to new firms in the same location. In that case, the spatial concentration of an industry may emerge and persist even when localization economies are negative (Appold, 1995; Sorenson and Audia, 2000; Staber, 2001; Stuart and Sorenson, 2003; Boschma and Wenting, 2007; Wenting, 2008). However, little attention has been drawn to merger and acquisition (M&A) activity in this literature. In this study, we argue that M&As may be regarded as an additional driver of spatial clustering of an industry. To our knowledge, this has not yet been investigated systematically with firm-level data over a long period of time.

This chapter investigates the spatial evolution of the Dutch banking industry between 1850 and 1993. In particular, we analyse the extent to which M&As within the industry have contributed to its spatial concentration in the Amsterdam region, where more than half of all banks in the Netherlands were located in 1993. The banking industry is a very interesting case. About half of all exits of banks in the Netherlands have been due to mergers with and acquisitions by other banks between 1850 and 1993. This number is much lower in other industries that have been investigated so far, where the number of exits due to M&As is around 5 percent (e.g., Klepper, 2002, 2007; Boschma and Wenting, 2007). The banking industry is also interesting because it is a knowledge-intensive service industry where most studies in this literature have investigated the spatial evolution of manufacturing industries, exceptions being Fein (1998), Pratt (1998), Consoli (2005), Grote (2008), Wenting (2008), Heebels and Boschma (2011) and De Vaan, Boschma, and Frenken (2013). The analysis is based on a unique database of all entries and exits in the Dutch banking industry collected by the authors. We focus specifically on the M&A activity of Amsterdam banks between 1850 and 1993 to see whether they have been disproportionally active in M&As. By means of survival analysis, we test whether being located in Amsterdam as such and whether having experience in M&As have affected the survival chances of banks in the Netherlands.

The structure of the study is as follows. The next section develops a perspective on the spatial evolution of industries when discussing M&A activity as a possible source of spatial clustering. Following that section, the data on the Dutch banking industry between 1850 and 1993 is introduced. The evolution of the Dutch banking industry and its concentration in the Amsterdam region is then described. The extent to which M&As have contributed to the spatial clustering of the Dutch banking industry is examined in the next section. The final section concludes and discusses the implications for future research.

4.2 M&A activity and the spatial clustering of an industry

Many studies have focused on localization economies and spin-off dynamics as explanations for the spatial clustering of an industry over time. Localization economies are about the benefits firms accrue from being co-located with other firms in the same industry, due to a pool of specialized labor, the presence of specialized input suppliers, and access to knowledge about the secrets of the respective trade (see, e.g., Maskell and Malmberg, 1999; Asheim and Gertler, 2005; Potter and Watts, 2011). This primary focus on localization economies has been challenged though, since the local presence of many competitors may produce high costs such as high labor costs and rents (see, e.g., Appold, 1995; Staber, 2001), and high numbers of exits (Sorenson and Audia, 2000; Buenstorf and Klepper, 2009; Heebels and Boschma, 2011). Other scholars have proposed that spin-off dynamics drives the spatial clustering of an industry (Arthur, 1994; Cantner et al., 2006; Klepper, 2007; Buenstorf and Klepper, 2009). In this view, spatial clustering of an industry emerges because of the entry of successful spin-offs that give birth to other successful spin-offs in the same location (Klepper, 2007, 2010; Boschma and Wenting, 2007; Heebels and Boschma, 2011; De Vaan et al., 2013). This is because the more spin-offs enter the region, the higher the probability that more spin-offs are generated (Arthur, 1994) and because (tacit) knowledge is transferred from parents to spin-offs, which positively affects their performance (Helfat and Lieberman, 2002; Klepper, 2007).

Little attention has been drawn to M&A activity as another possible explanation of spatial clustering of an industry (see, e.g., Markusen, 1985; Chapman, 1991, 2003). This may be due to the fact that most empirical studies on spatial clustering have focused on industries in which very few M&As occurred over time. For example, the percentage of firm exits due to M&A activity was only 6 percent in the U.S. automobile industry between 1895 and 1966 (Klepper, 2002, 2007), 5 percent in the British automobile industry between 1895 and 1968 (Boschma and Wenting, 2007), and 5 percent in the global fashion design industry between 1858 and 2005 (Wenting, 2008). In the banking industry, this figure is much higher. In the Netherlands, about half of all exits in this industry between 1850 and 1993 have been due to M&As. Hence, M&As may have had a distinct influence on the spatial evolution of the banking industry.

There is a huge literature explaining why firms engage in M&As. In general, this literature shows that increasing market power, achieving economies of scale or scope, diversifying into new products or services, and replacing inefficient management are important motivations. The specific determinants of M&As are also strongly industry-specific (Yin and Shanley, 2008). Regarding the banking industry, most studies have focused on the importance of bank-specific determinants (e.g., capital-asset ratio, liquidity, loan activity) and country-level determinants (e.g., liquidity regulation, deposit insurance schemes, disclosure requirements, disciplinary power of supervisory agencies), with mixed results so far (Pasiouras et al., 2011). When it comes to the study of spatial determinants of M&As, most studies have investigated whether spatial proximity between acquirers and possible targets increases the probability of M&As taking place (for an overview, see, e.g., Ragozzino, 2009). Few studies though (e.g., Markusen, 1985; Chapman, 1991, 2003) have yet investigated the long-term spatial implications of M&As, specifically as to what extent M&A activity contributes to the spatial clustering of an industry over time.

We expect M&A activity to contribute to the spatial clustering of an industry for two reasons. The first reason is that we expect that cluster firms are disproportionally more active than noncluster firms in undertaking M&A activity.[1] As M&As are a way for firms to expand and grow, firms in clusters have more opportunities to acquire other firms because there are more candidates around from the same industry. When the acquiring and the acquired firm share the same location, they are more likely to know each other well, with a reduction of uncertainty and an increased chance of an M&A taking place as a result. Geographic proximity has been shown to be an important driver of M&As between different industries within countries (e.g., Rodríguez-Pose and Zademach, 2003), within places (Böckerman and Lehto, 2006), as well as for M&As occurring within industries, as, for example, in the banking industry (Buch and DeLong, 2004; Felici and Pagnini, 2008; Wheelock and Wilson, 2004; Hannan and Pilloff, 2009). Furthermore, M&As might also be induced by strategies to enlarge a firm's market geographically by acquiring distant firms in markets the acquiring firm is not yet active in. Clustered firms might have a strong incentive to acquire nonclustered firms, because the competitive pressure in clusters is likely to be high, and banks in more peripheral regions may be relatively cheap (Burgstaller, 2013). Moreover, Colombo and Turati (2012) have argued that banks in the more developed areas with larger markets are also likely to be more efficient and profitable, and thus have more resources to finance the acquisition of other banks. This may be reinforced by the fact that clustering may lead to the local emergence of specialized services like consultants and lawyers specialized in M&A activity, which may further boost M&As by cluster firms. As a result, we expect that cluster firms are disproportionally more active in acquiring other firms - both in their own region and outside their region - as compared to noncluster firms.

The second reason why M&A activity may contribute to spatial clustering of an industry is that cluster firms are likely to perform better because of higher M&A experience. As firms in clusters are more likely to engage in M&As, cluster firms acquire more experience in M&As. This experience may enable cluster firms to reap the benefits from M&As more effectively, with a positive impact on their survival chances as a result. The benefits of having experience in M&As may be numerous. The acquisition of a firm can be considered a form of post entry learning in which acquiring firms get access to the knowledge of acquired firms, which may increase their own capabilities and improve their routines (Ahuja and Katila, 2001; Piscitello, 2004; Cassiman et al., 2005). An acquisition may also allow the acquiring firm to profit from internal economies of scale. Whether an acquirer is actually able to derive benefits from

1 We use the words "cluster" and "cluster firms" to refer to the place where the industry concentrates in space and to the firms in that industry that are located there, respectively. We do this for the sake of simplicity and are aware that the meaning of cluster may mean more than that and that its use in the literature has not been unproblematic (see Martin and Sunley 2003).

an acquisition depends on many factors such as the level of integration, the degree of top management replacement, the extent of resource relatedness between the acquirer and the acquired firm, and the resource quality of the acquired firm (see, e.g., Zollo and Singh, 2004; Cartwright and Schoenberg, 2006). In the long run, the ability of a firm to effectively cope with those factors depends on the experience it already has in M&As. This experience may be crucial in ensuring that an acquisition is well implemented and actually brings value to the acquiring firm. Therefore, we expect that having experience in M&As has a positive impact on a firm's survival chance. In turn, such experience in M&As accumulates mainly in clusters, as we expect that cluster firms are more likely to undertake M&As.

We expect both reasons to be more relevant at a later stage of the life cycle of an industry when M&A activity is known to be most intense (De Jong, 1981; Markusen, 1985; Klepper, 1997). Once an industry has concentrated in space, we expect cluster firms to be more active in acquiring other firms, which results in a decreasing share of firms in that industry located outside the cluster. And as cluster firms acquire more experience in doing M&A activity, we expect them to have higher survival chances than other firms in that industry. All this will contribute to the further spatial clustering of the industry. We test these theoretical expectations by focusing on M&A activity in the Dutch banking industry over a period of almost 150 years.

4.3 Data

As it is our aim to analyze the role of M&As in the spatial evolution of the Dutch banking industry and its spatial concentration in the Amsterdam region, we collected data on the years of entry and exit of each bank that entered the industry in the Netherlands during the period 1850–1993, the location of the head office, and data on M&A activity in the Dutch banking sector. Particularly, we used sources from the Dutch Central Bank (DNB, 1987, 2000), the Dutch knowledge institute on the financial sector NIBE-SVV (Kymmell, 1992, 1996; Geljon, 2005), chronicles on the history of the Dutch banking sector (De Jong, 1967; De Vries, 1989), the online databank on Dutch entrepreneurs of the Internationaal Instituut voor Sociale Geschiedenis [International Institute for Social History], trade journals, and chronicles on the history of particular banks.

Our data sources cover the period 1850–1993. Hence, we do not analyse the full life cycle of the Dutch banking industry, which is much older and goes back to at least the seventeenth century when Amsterdam was a leading international financial centre (Israel 1995). Consequently, our study covers only part of the life cycle of the Dutch banking industry but nevertheless the most interesting part from our perspective, as almost all M&As occurred in this period. Before 1860, a modern banking sector, one that takes deposits and grants credit to private enterprises, was practically non-existent in the Netherlands, although there was a money and stock market. The national bank, "de Nederlandsche Bank," was still the largest commercial bank in the country at that time (De Vries, 1989). This changed in the early 1860s, when the Bank Act of 1863 was enacted (Mooij and Prast, 2003) and when the first banks with a juridical structure of a limited liability company were created. This meant that large sums of capital to invest became available, which was completely new to the Dutch banking system at that time.

Our database includes a total number of 718 banks that entered the Dutch banking industry between 1850 and 1993. We have information on the headquarters of these banks, not on their branches. Hence, we are dealing with the most knowledge-intensive part of this service industry where high-order firm-specific routines are formed. For 112 banks, we were unable to identify the year of entry. Of all banks, 611 banks exited the banking sector in the period 1850–1993, 107 banks were still active in 1993. Of those 611 exits, 322 exits were due to bankruptcy, closure, diversification into other activities than banking, and so on. The other 289 exits were caused by M&A activity, which is about half of all exits in the Dutch banking industry.

4.4 Evolution of the Dutch banking industry

Figure 4.1 presents the evolution of the Dutch banking industry in terms of total numbers of entries, exits, and firms in the period 1850–1993. The number of firms and number of exits are somewhat underestimated in the first decades after 1850 because we do not have information on banks that were founded before 1850. Figure 4.1 shows that, except for a short intermezzo during the First World War, the total number of banks increased till 1929. What is remarkable is that the number of exits was extremely low in the second half of the nineteenth century. Entry levels were a bit higher but also remained low till the 1890s. This has been attributed to, among other reasons, the low tendency of firms to lend money from banks, because in the second half of the nineteenth century, that was considered a sign of weakness (Nierop, 1972). Since the 1890s, however, there has been a sharp and steady increase in the number of entrants, until the 1930s, when entry levels dropped sharply and remained low ever since. The number of exits also started to increase around the turn of the century but especially in the 1920s and early 1930s, which also led to the institutionalizing of formal supervision to prevent bank runs (Mooij and Prast, 2003).

At the turn of the century, the industry was dominated by five banks: Nederlandsche-Handelmaatschappij, Twentsche Bank, Rotterdamsche Bank, Amsterdamsche Bank, and Incasso Bank. In 1900, their total market share was 35 percent, which rose further to 48 percent in 1918 but fell down again to 38 percent in 1928. In 1930, the number of exits overtook the number of entrants, and the shakeout of the industry started. In 1940, the market share of the big five had risen to 52 percent (Kymmell, 1996). The declining trend in the number of firms decelerates in the 1970s. In the 1970s, there is a short increase in exit levels, after which the number of exits stabilizes at a low level. In 1993, there were 107 banks left. By that time, the Dutch banking industry had evolved into an oligopoly dominated by three banks (ABN-AMRO, ING Group, and Rabobank), which had a total market share of 80 percent (Van der Lugt, 1999; Bos, 2004).

Figure 4.1: The number of firms, entrants and exits in the Dutch banking industry, 1850–1993

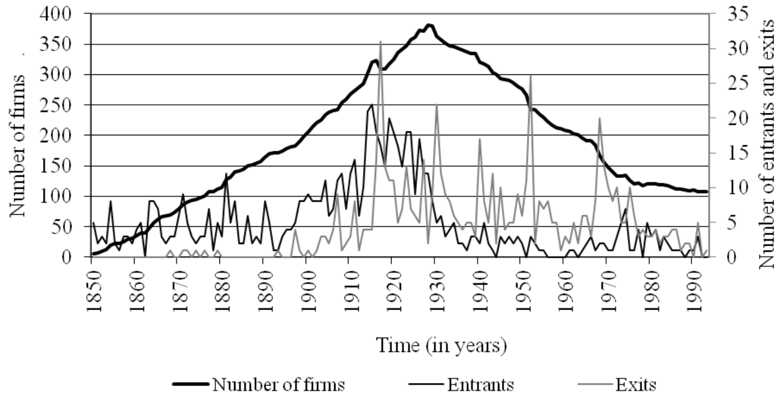
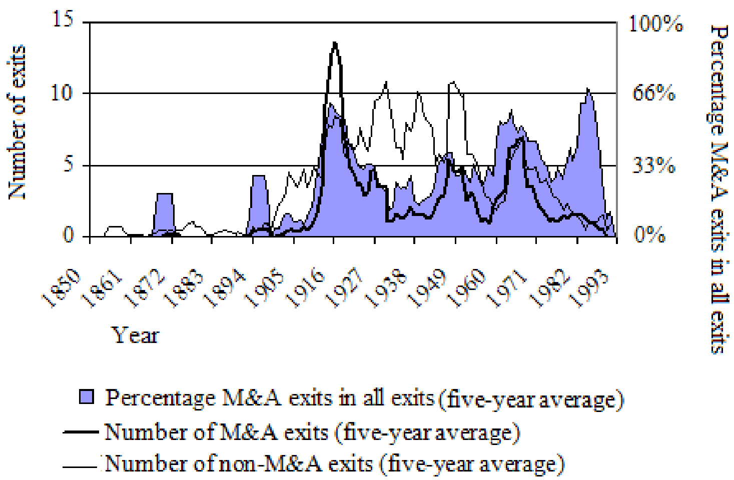


Figure 4.2 shows the number of exits due to M&A activity and their share in the total number of exits in the Dutch banking industry in the period 1850–1993. As explained earlier, about half of all exits were caused by M&As over this period, which is extremely high in comparison to other industries. M&A activity started around 1900, at a time when the industry was already well established, in terms of number of banks, and accelerated from 1920 onwards. In the early expanding phase of the industry from 1850 until 1910 hardly any M&As took place. M&A activity was highest in the period 1914–29, during which numerous small, mostly regional banks were acquired (Bosman, 1989). M&A activity slowed down after that, until a second wave of M&As occurred in the 1960s. From 1930 onwards, M&A activity resulted in a sharp decrease in the total number of banks, since the annual number of exits of banks exceeded the number of entries. ABN-AMRO became the largest bank in the Netherlands when ABN bank (itself a merger of Nederlandsche Handelmaatschappij and Twentsche Bank in 1964) and Amro Bank (a merger of Amsterdamsche Bank and Rotterdamsche Bank in 1964) merged in 1990 (De Vries et al., 1999; Jonker, 2003).

Figure 4.2: The number of exits due to M&As in the Dutch banking industry, 1850–1993.



In order to sketch the spatial evolution of the Dutch banking industry, we assigned the location (municipality) of all banks' headquarters to one of the 40 labor markets (COROP regions) in the Netherlands. In the very exceptional case that a bank moved from one region to another, we assigned the bank to the region where it had been active for most of the time. In Figure 4.3, we depict the evolution of the number of Amsterdam-based banks and banks located outside the Amsterdam region for the period 1850–1993. In Figure 4.4, we show the share of the four major bank regions of the Netherlands (i.e., the Amsterdam, Rotterdam, Utrecht, and The Hague regions)[2] in the national total for that same period.

Figure 4.3: Number of banks in and outside Amsterdam, 1850–1993

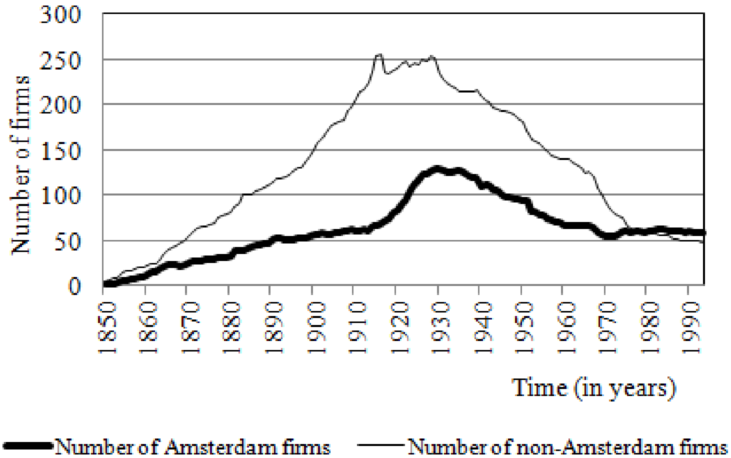
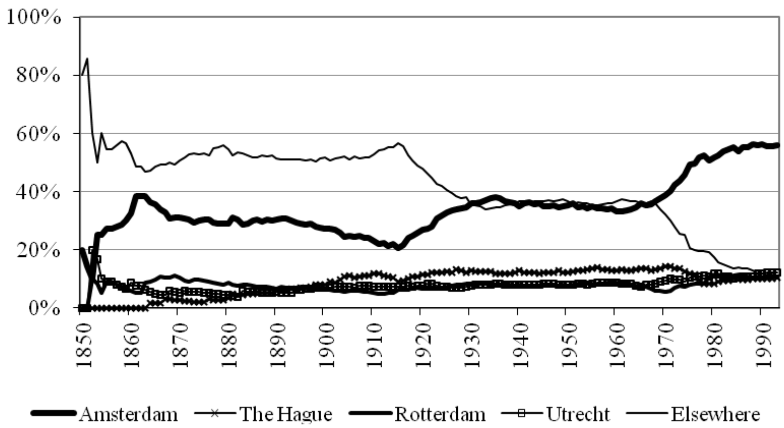


Figure 4.4: Shares of the four major urban Dutch regions in total number of banks, 1850–1993



2 Regions are so-called COROP regions, which correspond to labor market areas in the Netherlands. For instance, COROP region Groot-Amsterdam includes the city of Amsterdam and surrounding municipalities like Aalsmeer, Amstelveen, Diemen, Edam-Volendam, Haarlemmermeer, Purmerend, and Uithoorn.

As mentioned before, both figures include only banks that entered only after 1850, so the findings in the first decade after 1850 should be treated with caution. Figure 4.3 shows a steady increase in the number of banks in the Amsterdam region. Around 1900, as mentioned before, the Dutch banking industry was dominated by five large banks, of which four were based in the Amsterdam region. The increase in the number of banks in Amsterdam accelerated in the 1920s. After reaching a peak in 1930, a decline set in until the late 1950s, after which the number of banks stabilized at a level of about 60 to 80 banks till 1993.

In relative terms, as shown in Figure 4.5, the share of the Amsterdam region in the total number of banks dropped from 38 percent in the early 1860s to a mere 19 percent in 1915. This was not so much caused by exits of banks in Amsterdam but by a relative increase in the shares of the Rotterdam region (in the late 1860s) and The Hague region (in the 1900s). Till far into the 1910s, the majority of banks was still located outside the four major urban areas of the Netherlands. This picture changed after 1915, when 116 banks were founded in the Amsterdam region in just a period of 15 years, which increased its share to almost 35 percent in 1930. This share stabilized for almost 40 years, till foreign banks started to enter. In combination with exits that occurred mainly in the rest of the Netherlands, Amsterdam increased its share in the number of banks to around 56 percent in 1993. In terms of market share and corporate power, the concentration of bank activity in the Amsterdam region was much higher than that (Sluyterman et al., 1998). Hence, the regional share in number of banks is not equal to the regional market share, since the latter is even more spatially concentrated than the former. In the next section, we investigate the extent to which M&As within the industry contributed to the spatial clustering of the Dutch banking industry in Amsterdam.

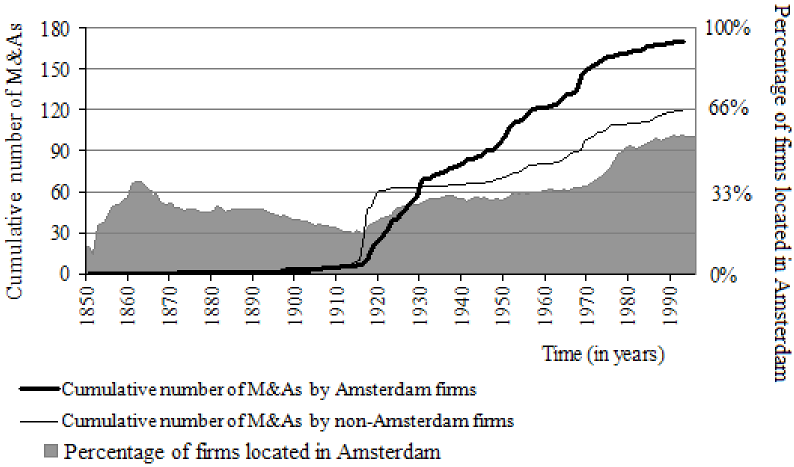
4.5 Empirical Findings on M&A Activity and Spatial Clustering

4.5.1 Are Cluster Firms More Active in Acquiring Other Firms?

To investigate whether cluster firms are more active in M&As, we focus on the M&A activity of banks in the Amsterdam cluster between 1850 and 1993. The first indication that M&A activity has contributed to the spatial concentration of Dutch banking in the Amsterdam region is shown in Figure 4.5, where the cumulative number of M&As by Amsterdam banks, as compared to non-Amsterdam banks, is presented. The share of the Amsterdam region in the total number of banks in the Netherlands increased rapidly especially in the 1920s and the 1970s, from about 16 percent to 30 percent, and from 35 percent to about 50 percent, respectively. As shown in Figure 4.5, these two major jumps coincided with a tremendous increase in M&A activity undertaken by Amsterdam banks.

Another finding is that banks in the Amsterdam cluster were disproportionally more active in acquiring other banks from Amsterdam as well as in acquiring banks from outside Amsterdam. Fifty-seven percent of all M&As were initiated by Amsterdam banks in the period 1850–1993, while only 33 percent of all entrants was located in the Amsterdam region during that period. As Table 4.1 shows, of all acquisitions done within a COROP-region (that is,

Figure 4.5: The cumulative number of M&As by Amsterdam banks and non-Amsterdam banks, and the share of banks located in the Amsterdam region.



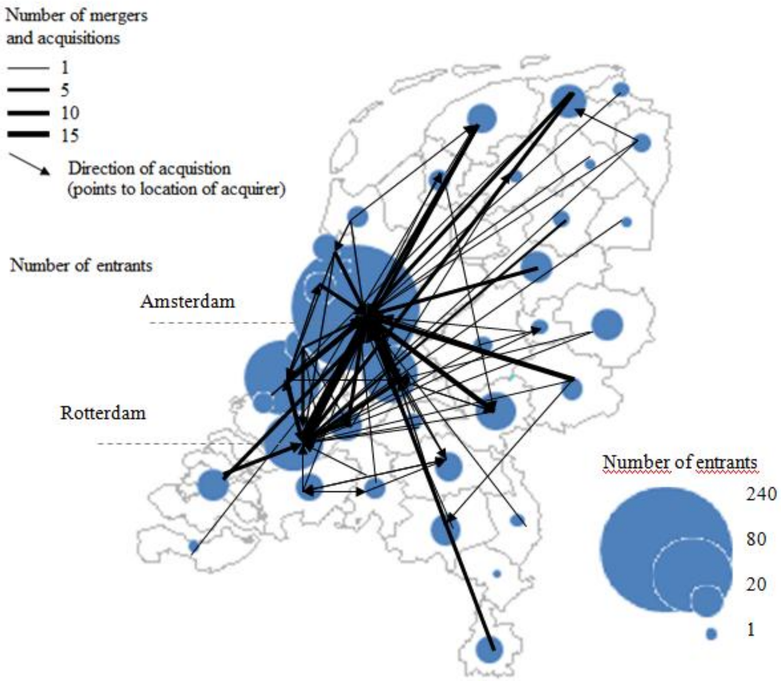
the acquired and the acquiring bank belonging to the same region), 64.5 percent of those intraregional acquisitions were done within the Amsterdam region. Having said that, most of the acquisitions by Amsterdam-banks (i.e., 76 percent) were acquisitions of other banks outside the Amsterdam region. Out of all acquisitions crossing borders of COROP regions (i.e., a bank acquiring a bank in another region), Amsterdam-based banks were again especially active: 55 percent of all interregional acquisitions were initiated by Amsterdam banks during the period 1850–1993.

Table 4.1: Intra- and Interregional Acquisitions: Numbers and Shares

	Number of M&As	Share of M&As
M&As within the region	61	21.4%
—by Amsterdam banks	40	64.5%
—by other banks	21	35.5%
M&As between regions	228	78.6%
—by Amsterdam banks	126	55.3%
—by other banks	102	44.7%
Total	289	100.0%

These results are further illustrated in Figure 4.6, which shows the number of entrants in the 40 Dutch COROP regions and the number of M&As (as depicted by the thickness of acquisition links) between those regions in the period 1850–1993. We see that M&As were mainly executed by banks in the Amsterdam region. The figure also shows that banks in more peripheral areas of the Netherlands were more likely to be victims rather than initiators of acquisitions. In sum, because of the disproportional amount of acquisitions by Amsterdam-based firms, we find strong evidence that cluster firms are indeed disproportionally more active in acquiring other firms (both in their own region and outside), as compared to noncluster firms. As set out earlier, this may be due to the fact that cluster firms have more opportunities to acquire other local firms, as compared to noncluster firms. And cluster firms might be subject to stronger competitive pressures and therefore have a greater incentive to acquire firms outside their region in order to enlarge their market.

Figure 4.6: Spatial distribution of M&As in Dutch banking industry, 1850–1993.



At the firm level, we examined which banks had been most active in doing acquisitions. When we ranked each bank in the Netherlands by the number of acquisitions in the period 1850–1993, the top seven were responsible for 57 percent of all acquisitions in the Dutch banking industry, and six of these banks were located in the Amsterdam region. In Table 4.2, we ranked the top five banks with respect to the number of direct and indirect acquisitions in the period 1850–1993. Direct acquisitions concerned the number of banks acquired, while indirect acquisitions were the number of banks acquired by another bank before this latter bank was acquired. As Table 4.2 shows, the top three banks were all located in the Amsterdam region, and they were responsible for 87 percent of all M&A activities in our research period. This seems to suggest that a cumulative mechanism in M&A activity is operating at the firm level. As M&As are complex processes, experience in M&As may have been beneficial, since it may have enabled these banks to derive more effectively the benefits of M&As, with a positive impact on their survival chances as a result. We investigate this issue in the next section.

Table 4.2: Top 5 Banks in the Netherlands: Share of Total Number of Direct and Indirect Acquisitions

Rank	Name of Bank	Share of M&A	Location
1	ABN AMRO	58.5%	Amsterdam
2	Fortis Nederland	15.7%	Amsterdam
3	ING Bank	12.5%	Amsterdam
4	Rabobank	3.0%	Utrecht
5	SNS Bank	1.2%	Utrecht

4.5.2 Do Firms with More Experience in M&As Have Higher Survival Chances?

To investigate whether experience in M&As positively affects the survival chances of firms, we employed survival analysis to estimate the probability of failure of banks. A duration variable was used that measures the length of time from the year of entry of the bank to the year of exit. Hence, the survival time is measured in years, and it is right-censored for banks that have survived until 1993. Each year a bank exists is considered as an observation (at time period t), and we estimate the probability the bank survives the next year (at time period t + 1), based on characteristics of the bank and its location at time period t. We include a number of control variables (age of the bank, whether a bank is foreign or not, time of entry) and allow the control variables to vary during the time period of observation. We estimate a competing risk model to distinguish exit due to failure from exit due to acquisition (survival is the reference category). Because of the discrete nature of the survival time in our data, we apply the discrete-time method used by Allison (1982) and extended by Jenkins (1995, 2005) to estimate the parameters of the model. This method approaches each type of event as taking place in continuous time between discrete observations, with specific hazard rates that remain constant within intervals. Jenkins (2005) shows that the multinomial logit model represents an accurate approximation in discrete time of a duration model (see, e.g., Cefis and Marsili, 2011).

To measure experience in M&As, we took the number of M&As done by each bank per year. For each year a bank exists, we counted the number of banks it acquired, including all banks it acquired in previous years. This cumulative number was transformed on a logarithmic scale to take into account diminishing returns to scale (Ln_cumM&A). We control for factors that are included in other duration studies on the evolution of industries (e.g., Klepper, 2007). Those are the location of a bank in the Amsterdam cluster (Amsterdam), the age of a bank (ln_t), whether a bank is foreign (FOREIGN), and the time at which a bank enters the industry. Time of entry has been defined according to four entry cohorts. COHORT 1 covers all banks entering during the period 1850–1913, which was a period when the Dutch banking sector was characterized by smallness and low levels of competition, which allowed banks to grow and expand. COHORT 2 concerns firms that entered during a very turbulent period in the

Dutch banking sector from 1914–29, during which scale economies grew in importance, entry barriers rose, and M&A activity was very intense. COHORT 3 captures banks that entered during the Great Depression and World War II (1930–45). COHORT 4 covers entrants in the post–WWII period and is treated as the reference category. We run the estimations with 712 banks for which we had information on all those variables. Because we have a large number of banks with a high average age, the total number of observations is 27,222. Descriptive statistics of the independent variables as well as their correlations are provided in Table 4.4 and Table 4.5 in the Appendix 4.A.

The results of the survival analysis are presented in Table 4.3. Having experience in M&As lowers the chance of failure for banks. As expected, the coefficient of the cumulative number of M&As is negative and significant. However, our findings show no effect of having experience in M&As on the probability of being acquired. Another interesting finding is that the cluster effect (as proxied by the Amsterdam dummy) is positive and significant for the probability of failure but negative and significant for the probability of being acquired. Apparently, being located in the Amsterdam region increases the chances of failure for banks but decreases the probability of being acquired. This finding tends to indicate that the spatial clustering of the Dutch banking industry was not driven by the fact that banks performed better in the Amsterdam cluster. Rather the contrary; the Amsterdam region turned out to be a very selective environment. Instead, as we showed earlier, clustering is a result of the fact that banks in Amsterdam have been disproportionally active in acquiring banks from other regions.

Our findings also show that younger banks were more likely to fail, while older banks were more likely to be acquired. And foreign banks showed a lower probability of failure. Early entrants outperformed late entrants, which is as expected, as far as COHORT 1 is concerned, because this period, 1850–1913, was a period of relatively weak selection. Banks belonging to COHORT 2 were more likely to be acquired though, since they entered during a period with a high intensity of M&A activity. We also added interaction terms of the Amsterdam dummy with the Cohort 1 and 2 dummies. Interestingly, while Cohort 1 and Cohort 2 banks had a lower probability of failure in general, this negative effect disappeared for Cohort 1 and 2 banks located in the Amsterdam cluster.

In the analyses above, we have not controlled directly for the size of banks (e.g., total assets), since those data are not available for all banks over time. The cumulative number of M&A variables may partly capture a size effect, since it reflects an increase in the size of banks due to previous acquisitions. The results of previous empirical studies on banks that did measure size are ambiguous regarding the effect of size on the probability of exit due to failure or acquisition. Wheelock and Wilson (2000) found no robustly significant relationship between size and the probability of failure of U.S. banks between 1984 and 1993. As for exit due to acquisition, they found that smaller banks are more likely to be acquired than larger banks. Lanine and Vennet (2007), on the contrary, found, in the case of cross-European deals between 1995 and 2002, that larger banks are more likely to be acquired than smaller banks. Hannan and Pillof (2009) found a similar result in the case of U.S. banks between 1996 and 2005, except only when acquisitions by small banks are taken into account. A reason for these differing results may be that, on the one hand, smaller banks are more attractive acquisition targets, since they are less expensive to acquire and can be more easily integrated into the acquiring bank, and the acquisition of smaller banks may raise fewer concerns by antitrust authorities. On the other hand, larger banks may be more attractive when one seeks economies of scale or market power, which is likely to be achieved at a lower cost by acquiring one large bank than a number of small banks. Hence, size may play a role in M&A activity of banks, but there seems to be no univocal relation between the two.

Table 4.3: Estimates of Probability of Exit Due to Failure and Due to Acquisition for Banks in the Netherlands, 1850–1993 (“Survival” is the Reference Category)

Variable	*Dependent Variable: Probability of Exit Due to Failure*	*Dependent Variable: Probability of Exit Due to Acquisition*
Ln_cumM&A	-0.689** (0.271)	0.168 (0.118)
Amsterdam	0.330** (0.135)	-0.682*** (0.182)
ln(t)	-0.129** (0.057)	0.250*** (0.068)
Foreign	-1.255** (0.509)	-0.140 (0.363)
Cohort 1 (1850–1913)	-1.151*** (0.217)	-2.874*** (0.463)
Cohort 2 (1914–29)	-0.610*** (0.211)	0.525*** (0.154)
Cohort 3 (1930–45)	0.018 (0.139)	-0.780*** (0.194)
Amsterdam *Cohort 1	-0.626 (0.402)	-1.787 (0.633)
Amsterdam *Cohort 2	-0.538 (0.372)	-1.091** (0.432)
Constant	-3.698*** (0.229)	-4.845*** (0.277)
LR chi2	340.96***	
Log likelihood	-3149.369	
Observations	27.222	

Significant at 95%; * Significant at 99%; Standard errors in parentheses

4.6 Conclusion

This study has investigated the extent to which M&As contributed to the spatial clustering of an industry. We analysed the spatial evolution of the Dutch banking industry and its spatial concentration in Amsterdam for a period of almost 150 years. One could argue that the leading role of the Amsterdam banking cluster was a continuation of what has happened long before, since Amsterdam has been part of a very long-term development that goes well back into the seventeenth century when financial services in Amsterdam were world-leading (Israel, 1995). Having said that, we have seen a further spatial concentration of the Dutch banking industry in the twentieth century, which calls for further clarifications.

Our study showed that M&A activity played an important role in the spatial clustering of the Dutch banking industry in the Amsterdam region during the twentieth century. Banks in Amsterdam were extremely active (disproportionally so) in acquiring other banks not only in their own region but also outside their region, as compared to noncluster firms. Amsterdam banks had more opportunities to acquire other local banks for sure. At the same time, due to stronger competitive pressure in the cluster, Amsterdam banks might have had greater incentives to acquire banks outside their region, in order to expand and enlarge their markets. The Amsterdam location may have contributed to this disproportionate M&A activity because of the local presence of services specialized in M&As and other financial organizations like the Dutch Central Bank. We also observed that only a small number of banks was responsible for the majority of all acquisitions, and those banks were almost entirely Amsterdam-based. In other words, those banks accumulated much experience in M&As over time. As M&As are complex processes, this experience may have been beneficial, since it may have enabled them to derive benefits from M&As more effectively. The survival analysis provided some evidence for this: the more experience a bank had in acquiring other banks, the lower its failure rate. By contrast, we found that being located in the Amsterdam banking cluster did not lower, but, instead, increased the failure rates of banks. Overall, these findings tend to suggest that the spatial clustering of the Dutch banking industry was not driven by the fact that banks on average performed better in the Amsterdam cluster. Instead, what contributed to the further spatial concentration of the Dutch banking industry was the fact that banks in Amsterdam acquired a disproportionate amount of banks elsewhere in the Netherlands. Moreover, the accumulation of experience in M&As took place mainly in Amsterdam, which in turn had a positive impact on the survival chances of banks located there.

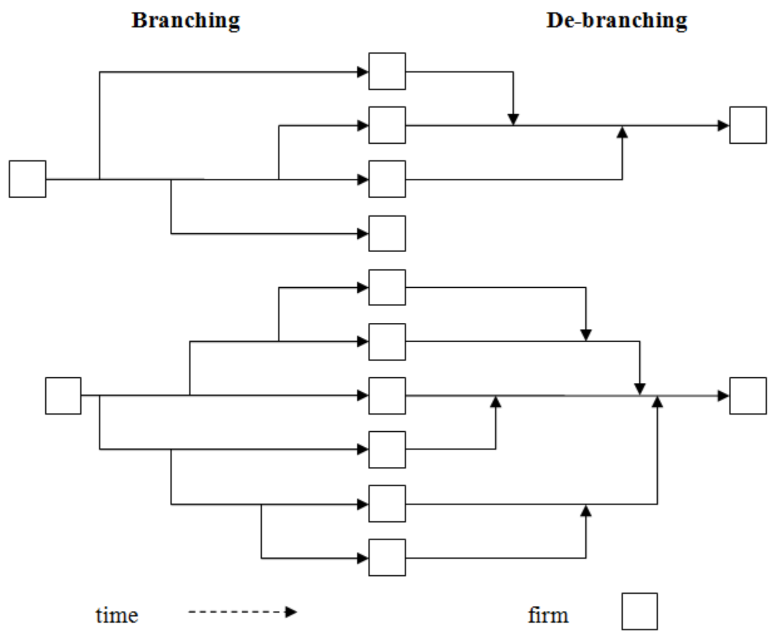
As any other study, these findings open up a number of new research challenges. First, there is a need to replicate this study in other countries, especially where banking is spatially concentrated, like the United States (New York), the United Kingdom (London), and Germany (Frankfurt). It could be that different regulation and governance structures have different effects on the spatial implications of M&As. In this context, one could also account for the internationalization of the banking sector and how that has affected the evolution of the Amsterdam banking cluster (see, e.g., Engelen and Grote, 2009). In this study, foreign banks showed higher survival rates, and Amsterdam was blessed with a strong presence of foreign firms. This could be further explored in future research.

Second, it is worth investigating the extent to which changes in the banking system as a whole drive the spatial evolution of the industry. Dow (1999), for example, argues that regional banking systems go through different stages of development, ranging from an early stage in which banks serve mainly as financial intermediaries (lending out savings) to a late stage in which banks focus mainly on securitization and off-balance sheet activities—roughly a gradual shift from retail to investment banking. At an early stage, the focus on intermediation may imply that banks mainly serve local communities and hence are dispersed, whereas at a later stage the focus on liquidity and services rather than credit may imply that banks need good knowledge of potential (large) borrowers, which may result in the spatial concentration of the industry in large cities. Hence, it is worth investigating whether such changes of activities of individual banks, related to the banking system in general, have an effect on the spatial evolution of the industry.

Third, we need to investigate to what extent, and how, M&As act as transfer mechanisms of routines between firms, since this has remained a black box so far. It might be that M&A activity in the banking industry is much less driven by getting access to successful routines of other firms, as in high-tech sectors, but much more by conquering market shares from competitors. This may also help in unfolding the specific benefits that firms derive from having experience in acquisitions, which we found to have a positive impact on their survival. Fourth, it would be interesting to include networks as determinants of the survival chances of banks. Directorship interlocks between banks may be important determinants of acquisition decisions of banks, especially within regions where these networks are more likely to occur, and these networks may also affect the long-term survival of banks. Okazaki and Sawada (2011) found evidence that the quality of their network decreased the failure rate of banks. Such a network approach would add to our understanding of the spatial evolution of industries and clusters from an evolutionary perspective (Ter Wal and Boschma, 2011).

Fifth, this study has focused on M&A activity, while other studies have concentrated on the spin-off process, or on agglomeration externalities, to explain spatial clustering of industries. We need to develop a comprehensive theoretical model that incorporates and combines the role of cluster dynamics, network dynamics, spin-off activity, and M&A dynamics. From an industry life cycle perspective, we claim that when M&As act as transfer mechanisms of knowledge and routines, M&A activity can be viewed as a de-branching process in which the routines of various firms come together and merge, which leads to a decrease in the number of firm-specific routines in the industry over time. This is depicted on the right side of Figure 4.7. Through M&A activity, a lineage structure between firm-specific routines across space is formed as time goes by, since knowledge and routines are transferred from acquired to acquiring firms. The spin-off process also contributes to the evolution of this lineage structure, as shown on the left side of Figure 4.7. However, the spin-off process sets into motion a branching process in which routines are transferred from parents to spin-off firms, and that makes the number of firm-specific routines within the industry increase over time. Both knowledge transfer mechanisms are likely to contribute to the spatial concentration of an industry. This is because the spin-off process is a self-reinforcing and path-dependent process that occurs at the regional level in which a relatively small number of parent organizations give birth to a relatively large number of (successful) spin-offs. With respect to M&A activity, this is because intraregional M&As will primarily occur within clusters, while interregional M&As will concern mainly cluster firms that acquire noncluster firms. Spatial clustering is further reinforced by the fact that only a small number of cluster firms will do most of the acquisitions because of the experience in M&As they acquire with cumulative learning and further internal economies of scale as a result. In that respect, M&A activity delineates a lineage structure between firms that crosses regional boundaries and lowers the number of firms in an industry over time. This process leads to a further consolidation of the industry, since market power is dispersed among fewer firms, and market power is also likely to be concentrated among cluster firms. Hence, consolidation may have an aspect of spatial concentration to it. This is the opposite of the lineage structure caused by the spin-off process, which is mainly intraregional and leads to an increasing number of firms over time, and that also adds to spatial clustering.

Figure 4.7: Branching (through spin-off process) and de-branching (through M&A activity) of organizational routines across the industry life cycle.



Another theoretical challenge is to investigate whether spin-offs are more likely to be initiators or victims of acquisitions, especially with respect to the parent firm. Are parents more inclined to acquire their spin-off firms, or do spin-off firms more often acquire their parent?

Both could be expected because of high degrees of social and geographic proximity between the two. This could also play a role in the de-branching process outlined above. That is, while many spin-offs are generated by only a small number of successful parents, those successful parents may also have the tendency to acquire their spin-offs at a later stage. If that occurs, a perfect mirror image would arise between the branching and de-branching process.

Appendix 4.A: Descriptive statistics of and correlation among variables

Table 4.4: Descriptive Statistics of Variables Used in the Survival Analysis

	Mean	Standard Deviation	Minium	Maximum
Amsterdam	0.333	0.471	0	1
Foreign	0.031	0.173	0	1
Cohort 1	0.294	0.456	0	1
Cohort 2	0.197	0.398	0	1
Cohort 3	0.198	0.399	0	1
Ln_cumM&A	0.078	0.373	0	3.664
ln(t)	3.024	1.092	0	4.963

Table 4.5: Correlation Matrix of Independent Variables

	Amsterdam	Foreign	Cohort 1	Cohort 2	Cohort 3	Ln_cumM&A	ln(t)
Amsterdam	1.000						
Foreign	0.035	1.000					
Cohort 1	-0.074	-0.045	1.000				
Cohort 2	-0.058	-0.034	-0.319	1.000			
Cohort 3	0.032	-0.026	-0.321	-0.246	1.000		
Ln_cumM&A	0.125	-0.004	-0.122	-0.028	-0.013	1.000	
ln(t)	0.027	-0.057	-0.245	-0.171	0.030	0.203	1.000

5.

Agents of structural change: The role of firms and entrepreneurs in regional diversification

Co-authors: Frank Neffke, Ron Boschma and Martin Henning

5.1 Introduction

Penrose (1959) famously argued that firms can only sustain growth if they expand not just the scale of their production, but also the scope of production. What is true for firms holds at the aggregate level of the economies of cities (Jacobs, 1969): unless they diversify into new activities, cities will be unable to prosper in a changing competitive landscape.[3] However, unlike a firm, a city and its surrounding region do not act for themselves, but instead, they must rely on firms and entrepreneurs to introduce new activities and the resources these activities require. At the same, a region's resources may influence which type of activities local firms are more likely to develop. In this study, we develop a new methodology to measure and identify structural change in regions, which enables us to disentangle who is responsible for the most salient structural change in a region. Are entrepreneurs or existing firms the most important economic agents of change? Does novelty arise from local entrepreneurs and firms, or is it introduced by actors from outside the region? And, once introduced, how sustainable is this novelty?

Our study offers three contributions. Firstly, we explore to what extent the Resource-Based View (RBV) of the firm can be adapted to the aggregate level of regional economies. Although much of what we will argue is compatible with, and draws on, classical notions of spillovers, agglomeration externalities and clusters, the RBV has at least two features that make it attractive for organizing our thinking about local economies. For one, the RBV's explicit acknowledgement of the inherent specificity of many strategic resources offers a natural way to discuss, not just how much a region produces, but also what it produces, allowing us to focus not just on a region's growth but also on its direction of diversification. Given that many resources that firms use are embedded in the local context (such as skilled labor, infrastructure, knowledge institutes, suppliers, etc.), the services (Penrose, 1959) these resources provide are often more accessible from within the region, than from outside the region.[4] This suggests that regions can be conceived of as endowed with resource bases to which only local firms have easy access (Lawson, 1999; Boschma, 2004). Moreover, although the RBV's emphasis on rents to firm-owned resources would seem to preclude applying the framework to regions – which do not own resources – the discussion of rents actually has implications for which agents will be most dependent on locally available regional resources. We will show that these implications translate into testable hypotheses on which agents will induce most structural change.

Secondly, we introduce a new quantitative framework to infer how much structural change a region undergoes when new activities are added to its industry mix, where we define structural change as industrial change that involves a transformation of the local resource

3 As mentioned in the introduction of this PhD thesis, Detroit, for instance, went through a particularly devastating episode of this kind when the Great Recession hit the city's automotive industry so hard that it eventually defaulted on part of its debt (Pendall *et al.*, 2010).

4 That is not to say that these resources can only be accessed from within the region. For instance, firms that connect a region to the resources in other regions have been identified as highly valuable to the region's economy (e.g., Asheim and Isaksen 2002).

base. This framework relies on measuring how unrelated new activities are to the current local economy to infer the implied change they induce in the underlying resource base. Our study on Sweden for the period 1994 to 2010 shows that there is substantial churning of local industries and large shifts of employment between them, but most of these shifts take place among industries that are closely related. This suggests that the underlying resource structure changes much slower than a superficial analysis of employment reallocation would suggest.

Thirdly, we apply this quantitative framework to a comprehensive employer-employee linked dataset that covers every worker in the Swedish economy between 1994 and 2010 to study which types of agent induce most structural change in a region. We distinguish among five types of economic agents. First, we distinguish between the owners of existing establishments and the founders of new establishments. We find that incumbent establishments reinforce a region's existing resource base, whereas new establishments tend to induce structural change. Among the founders of new establishments, we further differentiate new establishments that belong to existing firms (new subsidiaries) from those that belong to entrepreneurs. We find that entrepreneur-owned establishments (i.e., start-ups) induce most structural change in the short run, but because entrepreneurs are more dependent for their survival on the presence of related activities in the region, new subsidiaries of existing firms assume this role increasingly as start-ups in unrelated industries fail. Finally, we subdivide both founder types into local and non-local founders. We find that non-local founders create only one third of all new-establishment employment, but they contribute 56% of such employment in the 5% of industries that are least related to the local economy. Radical structural change, therefore, predominantly depends on non-local firms and entrepreneurs.

5.2 Theory: a resource-based view of the region?

The resource-based view (RBV) of the firm (Wernerfelt, 1984; Barney, 1991) conceptualizes firms as bundles of resources. The RBV discusses identifies four characteristics of resources that are of particular interest to our theoretical framework. First, the RBV states that if resources are valuable, rare and hard to imitate and substitute, they confer sustained competitive advantage to their owners (Barney, 1991). Second, resources are often highly specific, because the productive services they yield (Penrose, 1959) can be applied in only a limited number of related activities. Indeed, this sharing of resource requirements is what makes activities related (Bryce and Winter, 2009). Third, as firms become better at exploiting the resources they use, more of these resources are left idle. Whenever a firm cannot expand its existing activities sufficiently to absorb these idle resources, it has an incentive to search for alternative applications that leverage these resources (Montgomery and Wernerfelt, 1989; Peteraf, 1993), which provides a rationale for related diversification (Penrose, 1959; Teece 1982). Fourth, long-term survival requires firms to renew their resource-base through dynamic capabilities (Teece et al., 1997).

Following Lawson (1999), we will argue that the notion of a resource base at least partially carriers over from firms to regions. This statement builds on the fact that each of the four elements of the RBV we discussed above translates to some extent to the regional context. That is, (1) like firm-internal resources, firm-external local resources, such as the local infrastructure, knowledge institutions, specialized labor markets, etc., can display characteristics that are typically associated with sustained competitive advantage; (2) such local resources are often specific, yet also fungible to a degree; (3) some of them grow when they are used more intensively; and (4) given that resources become obsolete with the inevitable changes in technologies and final demand, regions decline if their resource bases are not updated accordingly. As a consequence, some of the predictions about firm behavior that emerge from the RBV carry over to regions. In particular, observations (1) to (3) suggest that, like firm diversification, regional diversification is a path-dependent process, while observation (4) suggests that to avoid decline, regions must renew their resource bases just like firms have to reinvent themselves from time to time. Below, we will further articulate these statements.

5.2.1 Regional resource bases

The notion that firms co-develop with their local economies is by no means new. For instance, the interdependences between firms and their local environment have been described in terms of spillovers and agglomeration externalities (Alcacer and Chung, 2007; 2013; Delgado et al., 2012; Glaeser and Kerr, 2009; Glaeser et al., 2010). So what do we gain from bringing resource-based thinking to the regional context? The main benefit is that it offers a way to theorize about regional diversification. Indeed, although urban economist differentiate between benefits of local specialization (“MAR” externalities) and of local diversity (“Jacobs” externalities), these concepts do not explain regional diversification. Indeed, absent additional assumptions, the agglomeration literature typically remains agnostic about which new activities will arise in a region. Consequently, diversification, and in particular the notion of related diversification, play a relatively minor role in the urban economics literature.

That is not to say that the importance of related industries per se has remained unnoticed. Pioneering work on the role of inter-industry relatedness is found in cluster research (Porter, 1998, 2003; Maskell, 2005; Delgado et al., 2013). For instance, in line with the notion that that regions exhibit “geographies of scope” (Florida et al., 2012), the presence of related industries has been found to spur entrepreneurial activity (Delgado et al., 2010) and to increase manufacturing plants’ survival rates (Neffke et al., 2012). Similarly, Ellison et al. (2010) and Dauth (2010) use relatedness measures to disentangle externality channels. In spite of this research, the question of how relatedness affects diversification has not received nearly as much attention in the literature on regional growth as in work on firm growth.

Recently, however, this issue has received more attention. For instance, Frenken and Boschma (2007) and Boschma and Frenken (2011) argue that regional development resembles a branching process in which new, yet related activities spin out of existing activities. Empirical support for this conjecture is growing. At the national level, Hidalgo et al. (2007) show that countries diversify their export portfolios according to such a branching logic. Neffke et al. (2011) show that similar processes are at work in the long-term development of Swedish regions, a result that has been replicated for regions in Spain (Boschma et al., 2013) and the United States (Essletzbichler, 2013; Muneepeerakul et al., 2013).

Interestingly, this work on regional diversification implicitly acknowledges the existence and importance of regional resources. For instance, Boschma and Frenken refer to regional knowledge bases and institutions, whereas Hidalgo and co-authors explain their findings in terms of national capabilities, whereas Muneepeerakul et al. (2013, p. 1) refer to a city's "portfolio of technologies and skills."

What would such regional resources look like? Many authors stress the importance of skilled local labor markets, specialized suppliers and local knowledge (Glaeser et al., 1992; Henderson et al., 1995; Almeida and Kogut, 1999; McCann and Simonen, 2005; Faggian and McCann, 2006). In cluster research, elements of Porter's (1990) diamond, such as the availability of production factors and the non-traded goods and services of supporting industries are singled out (Porter 2003). Furthermore, economic geographers highlight the importance of regions' "untraded interdependencies" (Storper, 1995) or "localized capabilities" (Maskell and Malmberg, 1999), such as local knowledge bases, institutions and networks (Cooke and Morgan 1998; Boschma 2004; Asheim and Gertler 2005).

To what extent would these resources help local firms compete in global markets? From a resource-based perspective, they would need to be valuable, rare, inimitable and non-substitutable. Many of the regional resources described above fit this definition. Firstly, that regional resources are often valuable and non-ubiquitous is all but beyond dispute. Secondly, analogous to the inimitability requirement, regional resources are often highly localized because many of them are not tradeable across places. However, regional resources are not necessarily non-substitutable, especially not if establishments can access firm-internal resources, a particularity to which we return later.

Apart from often being valuable, rare, non-imitable and non-substitutable, regional resources are often specific to the economic activities they are used in. For instance, specialized car parts suppliers are of little use to pharmaceutical firms. Likewise, skilled actuaries are valuable to local insurance companies, not to operators of spas. And just like firm-internal resources, external resources are also often somewhat fungible (Teece, 1982). For example, although the presence of skilled mechanical engineers may not be useful to all economic activities, their services are valued in multiple manufacturing and business services activities.

Finally, like firm resources, also regional resources sometimes grow the more they are used. For instance, skilled workers are attracted to places with matching employment opportunities. Similarly, specialized suppliers are attracted to regions that host potential clients. These processes are self-reinforcing: firms that use specialized resources are attracted to regions where these resources are available, while specialized resources are attracted by the presence of firms willing to pay for them (Duranton and Puga, 2004). Accordingly, regions grow for similar reasons that firms do: regions host resources that expand with their use and are valuable, rare, specific to the existing economic activities and hard to access from outside the region.

5.2.2 Industrial change versus structural change

However, economic environments are not static. Changes in technologies and demand can render existing resources obsolete and erode incumbent firms' competitive advantage (Tushman and Anderson, 1986). This has raised interest in so-called dynamic capabilities, capabilities that not just help firms diversify into new products, but also rearrange the underlying resource configurations (Henderson and Cockburn, 1994; Teece et al., 1997; Eisenhardt and Martin, 2000; Helfat and Peteraf, 2003).

Resource obsolescence does not only affect firms but also regions (Grabher, 1993; Pouder and St. John, 1996; Glaeser, 2005). Once existing regional resources become insufficient for local firms to compete at global markets, the regional resource base must be renewed or lose its attraction. Just like "new resource configurations" (Eisenhardt and Martin, 2000) go beyond changing a firm's product portfolio, renewal of the regional resource base goes beyond a mere change in the region's industrial employment composition. We therefore distinguish between regional diversification that merely changes the local industry composition and to which we refer as industrial change, and the unrelated regional diversification that requires a transformation of the local resource base. Only the latter type of diversification do we call structural change.

5.2.3 Rents to regional resources and agents of structural change

Because the resource base is affected by the production decisions of local firms, the regional counterpart to dynamic capabilities (Teece et al., 1997) resides in how local economic agents expand or scale down existing economic activities. However, in spite of their commonalities, regional and firm resource bases differ in at least two ways. First, regional resource bases do not develop by the volition of a central actor. Instead, a region depends on firms and entrepreneurs to introduce new productive resources and retire old ones.[5] Second, because firms control their internal resource bases, they can often extract rents from them. In contrast, it is not obvious who will appropriate the rents of a regional resource base, which, in principle at least, is available to all local firms. Therefore, although local firms may gain a competitive advantage over firms outside the region, a priori, firms in the same region are at "competitive parity" (Pouder and St. John, 1996, p. 1203). Consequently, if firms can freely enter a region, the rents of a superior regional resource base do not necessarily accrue to local firms. Instead they may end up with the owners of local production factors with a relatively inelastic supply,

5 That is not to say that firms and entrepreneurs are the only actors that matter. Other actors, like universities and governments, may facilitate diversification processes. However, in the end, it is firms who hire the workers and create employment in new economic activities.

such as labor or land.[6]

However, the relation between resources and rents is still useful, because the assumption of competitive parity is unlikely to hold perfectly. In particular, economic agents differ in the extent to which they (1) can access regional resources, (2) have access to resources outside the region and (3) have to rely on regional resource.

We distinguish among a number of different types of economic agents. Firstly, we distinguish among a region's existing establishments and its new establishments. Furthermore, new establishments either belong to existing firms or to entrepreneurs. Finally, these existing firms and new entrepreneurs originate from either inside (local agents) or outside the region (non-local agents).

Who of these agents are most likely to introduce new resources to a region? As mentioned above, agents firstly differ in their access to regional resources. As firms grow deeper roots in a region accessing regional resources becomes easier (Grabher, 1993; Pouder and St. John, 1996; Storper and Venables 2004). For one, preferred access to local suppliers may require long-standing relationships (Ghemawat, 1986) and the same holds for local knowledge networks (Giuliani, 2007). For another, the (often localized) social networks give local firms an edge over newcomers in finding suitable workers (Sorenson and Audia, 2000). Indeed, Dahl and Sorenson (2012) show that experience in the region, is almost as strong a predictor of an entrepreneur's success as experience in the industry. If firms with developed ties in the region indeed can access local resources more easily, such firms would also be more likely to build on existing local resources, instead of introducing new ones. This argument is resonates with the organizational ecology literature's insight that incumbent firms are less likely to introduce major changes due to entrenched routines, as compared to new firms (Hannan and Freeman 1984), and that when they do, they diversify in more related activities (Teece et al. 1994). This suggests the following hypothesis:

Hypothesis 1: Incumbent establishments are less likely to induce structural change in the region than new establishments.

Agents do not only differ in terms of access to local resources. For one, some firms have networks that allow tapping into resources outside the region more easily than other firms. Through such networks, such firms can access knowledge and resources required in activities that do not yet exist in their local economies. For another, several scholars (e.g., Storper, 1995; Pouder and St. John, 1996, Lawson and Lorenz, 1999; Gertler, 2003; Boschma, 2004) argue that local firms often follow the same dominant logic or even get locked-into local "groupthink" (Grabher, 1993). This would make local firms more likely to perpetuate the existing resource base. In contrast, agents that enter the region from elsewhere, may not only lack access to some of the resources in their new region, but also infuse their new region with ideas, skills and relations to other regions. Taken together, this suggests that local agents

6 Indeed, urban economists often seek (and find) evidence for agglomeration externalities in elevated wages or house prices instead of in the profits of local firms (Rosenthal and Strange, 2004; Glaeser, 2005).

are less likely to change the region's resource base than agents that enter the region from elsewhere:

Hypothesis 2: New establishments of local entrepreneurs and firms are less likely to induce structural change in the region than new establishments of non-local entrepreneurs and firms.

Finally, agents differ in the extent to which they depend on regional resources. In particular, new subsidiaries of existing firms often can access their parents' firm-internal resources as a substitute for regional resources. [7] This is a classical argument championed by the international business literature to explain the internationalization of firms (Iammarino and McCann, 2013). Such subsidiaries can therefore develop activities that rely on resources need not yet exist in the region. If these resources get transferred to the region, the regional resource base expands. This suggests that subsidiaries of existing firms would induce more structural change than entrepreneur-owned establishments, which are more reliant on regional resources because they lack access to resources of a parent-firm.

At the same time however, there is a long history of thought that associates entrepreneurship with structural change. Since Schumpeter (1934), entrepreneurship has been associated with new combinations, innovation, and structural change: entrepreneurs are typically more risk-taking (Cramer et al., 2002) and creative (Zhao and Seibert, 2006) than the average person. Given these contradictory considerations, both (opposing) hypotheses are justifiable:

Hypothesis 3a: New establishments of entrepreneurs are less likely to induce structural change in the region than new establishments of existing firms.

Hypothesis 3b: New establishments of existing firms are less likely to induce structural change in the region than new establishments of entrepreneurs.

5.3 Methodology

5.3.1 Data

We test these hypotheses on data derived from the administrative records of Sweden for the years 1994 to 2010.[8] These records contain information on wages and private-business income for all working-age individuals living in Sweden. Individuals are linked to establishments, and establishments are linked to parent firms. For establishments, we know its industry affiliation and in which of Sweden's 110 labor market areas it was located. We define industries at the 4-digit level (which distinguishes over 700 different industries) of the

7 Indeed, subsidiaries draw fewer externalities from the local environment than stand-alone establishments do (Henderson, 2003).

8 Data access was provided by Statistics Sweden (SCB). Further information on data access and a detailed documentation of the data can be found on the SCB website (SCB, 2011).

European NACE classification, which changes very little over the period we analyze.

An important assumption in this study is that locally available resources influence an establishment's location choice. However, in some industries, location choice is severely restricted because of the need to be close to natural resources or the large numbers of customers in urban agglomerations. Therefore, we define a region's industry mix based on 259 traded, non-natural-resource-based industries in the private sector, excluding non-traded services (e.g., retail stores and restaurants), government activities and natural-resource-based activities (e.g., mining and agriculture).[9] On average, these activities represent 29.8% of all private-sector employment in Sweden in the period of our study.

5.3.2 Measurement

Testing the hypotheses of section 5.2.3 requires us to quantify by how much each agent type diversifies the regional resource base. We already introduced the distinction between industrial and structural change. However, the word "diversification" can also be used either in a static sense ("How diversified is a region?") or in a dynamic sense ("By how much did the portfolio of local economic activities change?"). This leaves us with four different, yet related, concepts to quantify (see Table 5.1). Firstly, there is a static concept of industrial diversity, which can be measured by the number of different industries in a region or by the entropy of the employment distribution across industries. Secondly, the dynamic notion of industrial change refers to shifts in a region's industrial composition, and can be measured by entry and exit rates of industries or by the cosine distance of a region's industrial employment vector vis-à-vis a base year. Moving from activities to resources, the static notion of diversification refers to the coherence (or lack thereof) of regional economic activities in terms of shared resource requirements. It is important to note that coherent regions are not necessarily better off than incoherent regions. Although, the compact resource base of coherent regions is easier to maintain it also limits the diversification options. Therefore, intermediate levels of coherence may be optimal in the long run, in the same way that there is an optimal level of diversification for firms (Palich et al., 2000). Finally, there is a dynamic counterpart to the notion of coherence, which we call structural change. Structural change refers to the change in resource requirements that underlies a change in economic activities (i.e., that underlies industrial change). Similarly to coherence, structural change is not necessarily desirable. Region's resource structures can improve as well as deteriorate, an issue to which we return shortly.

What complicates measuring coherence and structural change is that we do not observe regions' actual resource bases, let alone changes therein. What we do observe is a region's industry mix. For the industries in this mix, it holds that to be active in an industry, firms must (by definition) have access to the resources this industry requires. Some of these resources will be firm-internal, but others will be regional resources (such as qualified labor, dedicated infrastructure and specialized suppliers) that are also available to other local

9 Details are provided in Appendix 5.A.

Table 5.1: Diversity, industrial change, coherence and structural change

	Static	Dynamic
Industries	***Diversity*** **Measured by:** entropy **Underlying question:** How many different industries are there and how equal is their size distribution?	***Industrial change*** **Measured by:** cosine distance **Underlying question:** How fast are new industries introduced and how much does the size distribution of activities change?
Resources	***Coherence*** **Measured by:** see Table 5.2 **Underlying question:** How similar are the resources required by the various industries in the region? That is, how related are the industries in a region to one another?	***Structural change*** **Measured by:** see Table 5.2 **Underlying question:** To what extent does the resources base change due to changes in the region's industries? That is, how related are current industries to the industry mix in the base year?

firms. Although we do not have information on the exact nature of these resources, from the relatedness among industries, we do know which local industries share similar resources.[10]

This reasoning suggests an indirect way to measuring structural change. In particular, when a region diversifies into an industry that is unrelated to its current portfolio of industries, it typically draws on new resources. The introduction of these resources to the region expands the regional resource base. Therefore, even absent concrete information on resources, we can still quantify regional coherence using information on how related a region's activities are to one another. Similarly, the degree of structural change can be measured by investigating how unrelated a region's diversification is.

This indirect measurement involves four steps: (1) determining how related industries are to one another in terms of resource requirements. This industry-to-industry relatedness can then be used to calculate (2) how related an industry is to the basket of industries that constitute a region's industry mix. We call this the regional resource match, or simply the match of an industry to a region. Next, (3) regional coherence is quantified as the average resource match of all industries in the region. Finally, (4) structural change is defined as the match of the current industry mix to the region's past resource base. This procedure is summarized in Table 5.2 and explained in the following sections in detail.

Inter–industry relatedness

Inter-industry relatedness can be measured in several ways (see Ellison et al. 2010; Neffke and Henning, 2013). We focus on relatedness in terms of similarities in workers' skill requirements or skill relatedness (Appendix 5.C shows that our empirical findings also hold using other relatedness measures). Our focus on skills has two reasons. Firstly, the skills embedded in a firm's human capital are among its most valuable resources (Grant, 1996; Grant and Spender, 1996) and have been shown to condition a firm's diversification path (Porter, 1987; Neffke

10 Indeed, many authors *define* industries to be related if they require similar resources (Farjoun, 1994; Teece *et al.*, 1994; Bryce and Winter, 2009).

Table 5.2: Definitions and relationships among quantities

quantity	unit of analysis	Definition	description	normalization	range
labor low	industry-industry	F_{ij}	How many people change jobs from industry i to j?		[0, ∞)
skill relatedness	industry-industry	$SR_{ij} = \frac{F_{ij}}{F_{i.}F_{.j}} F_{..}$	How related are two industries to one another?		[0, ∞)
employment	industry-region	E_{irt}	How many workers does industry i employ in region r in year t?		[0, ∞)
related employment	industry-region	$E_{irt}^{rel} = \sum_j E_{jrt} I(SR_{ij} > 1)$	How much related employment to industry i exists in region r in year t?		[0, ∞)
resource match	industry-region	$LQ_{irt}^{rel} = \frac{E_{irt}^{rel}/E_{.rt}}{E_{i.t}^{rel}/E_{..t}}$	How overrepresented are related industries in the region?	$\widetilde{LQ}_{irt}^{rel} = \frac{LQ_{irt}^{rel}-1}{LQ_{irt}^{rel}+1}$	[0, ∞) norm.: [-1,1)
coherence	region	$C_{rt} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{irt}^{rel}$	How related are a region's industries on average to the regional economy as a whole?		
coherence baseline	region	$C_{rt}^{base} = \sum_i \frac{E_{i.t}}{E_{..t}} \widetilde{LQ}_{irt}^{rel}$	How related are the industries in the national economy to the regional economy?		[-1,1)
structural change	region	$S_{rt,T} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{irT}^{rel}$	How related are a region's current activities to the region's industry mix of year T?		[-1,1)
structural change by agent type	agent-region	$A_{rt,T}^{a} = \sum_i \frac{\Delta E_{irt,T}^{a}}{\Delta E_{.rt,T}^{a}} \widetilde{LQ}_{irT}^{rel}$	How related are the industries in which a given agent type creates or destroys employment to the region's industry mix of year T??	$\tilde{A}_{rt,T}^{a} = A_{rt,T}^{a} - C_{rT}$	[-1,1) norm.: (-2,2)

and Henning, 2013). Secondly, human capital can and is shared among firms in a region. It therewith acts as an important conduit of knowledge exchange and local externalities (Almeida and Kogut, 1999).

Skill relatedness among industries is measured by assessing the labor flows between industry pairs. In the period 1994 to 2010, about 4.5 million workers aged between 18 and 65 in Sweden switched jobs among different 4-digit industries. To avoid problems with missing industries, we keep only those industries that have nonzero employment in each year. First, we use equation (5.1) to calculate skill relatedness for every year between 1994 and 2010. Letting years be indexed by t and summation over omitted categories indicated by '.' this yields:

$$SR_{ijt} = \frac{F_{ijt}}{(F_{.jt}F_{i.t})/F_{..t}} \quad \text{(Eq. 5.1)}$$

Because this measure is highly asymmetric, we use the same transformation as in equation (4) to map it SR_{ijt} onto the interval [-1, 1):

$$\widetilde{SR}_{ijt} = \frac{SR_{ijt}-1}{SR_{ijt}+1} \quad \text{(Eq. 5.2)}$$

Hence, industry i is skill related to industry j if $\widetilde{SR}_{ijt} > 0$. Then, for every industry pair, we average $\widetilde{SR}_{ijt}$ over all yearly flows between 1994 and 2010:

$$M\widetilde{SR}_{ij} = \frac{1}{16}\sum_{t=1994}^{2009} \widetilde{SR}_{ijt} \quad \text{(Eq. 5.3)}$$

Finally, we symmetrize the measure so that $S\widetilde{SR}_{ij} = S\widetilde{SR}_{ji}$:

$$S\widetilde{SR}_{ij} = \frac{M\widetilde{SR}_{ij}+M\widetilde{SR}_{ji}}{2} \quad \text{(Eq. 5.4)}$$

The actual condition for two industries to be skill related that we evaluate in the indicator function in equation (2) is therefore $S\widetilde{SR}_{ij} > 0$.

Industry–region resource match

Skill relatedness characterizes industry-industry pairs. However, the relatedness of a local industry to its regional economy is an industry-region relationship. We quantify this relationship by calculating the amount of employment in a region that is related to an industry. The more related employment there is, the stronger the industry's match with the region's resource base is supposed to be. Let E_{irt}^{rel} be all employment in industries related to industry $\mathbf{i}$ in region $\mathbf{r}$ in year $\mathbf{t}$:[11]

$$E_{irt}^{rel} = \sum_j I(SR_{ij} > 1)\, E_{jrt} \tag{Eq. 5.5}$$

where E_{jrt} represents the employment of industry $\mathbf{j}$ in region $\mathbf{r}$ in year $\mathbf{t}$ and $I(SR_{ij} > 1)$ an indicator function that evaluates to one if its argument is true and to zero otherwise. The match of industry $\mathbf{i}$ to region $\mathbf{r}$ in year $\mathbf{t}$ is defined as the degree to which the region is overspecialized in industries related to industry $\mathbf{i}$. That is, it is based on the location quotient of related employment:

$$LQ_{irt}^{rel} = \frac{E_{irt}^{rel}/E_{.rt}}{E_{i.t}^{rel}/E_{..t}} \tag{Eq. 5.6}$$

where $E_{.rt}$ is the total employment in the region in year $\mathbf{t}$, $E_{i.t}^{rel}$ the total employment in related industries in the country, and $E_{..t}$ the overall employment in the country. If LQ_{irt}^{rel} is greater than one, the employment share of related industries in the region exceeds their share in the national economy. If it is smaller than one, the region has a smaller share of related industries than the national economy does. By construction, LQ_{irt}^{rel} has a strongly asymmetric distribution: whereas an overrepresentation of related industries ranges from 1 to infinity, the underrepresentation of related industries lies between zero and one. This asymmetry complicates calculating averages. We therefore transform LQ_{irt}^{rel} as follows:

$$\widetilde{LQ}_{irt}^{rel} = \frac{LQ_{irt}^{rel} - 1}{LQ_{irt}^{rel} + 1} \tag{Eq. 5.7}$$

$\widetilde{LQ}_{irt}^{rel}$ ranges from -1 (no related employment) to +1 (a complete concentration of all related employment in region $\mathbf{r}$). Because $\frac{LQ_{irt}^{rel}-1}{LQ_{irt}^{rel}+1} = -\frac{(1/LQ_{irt}^{rel})-1}{(1/LQ_{irt}^{rel})+1}$, a given level of overrepresentation of related employment has the same magnitude but opposite sign as the same level of underrepresentation. For instance, if $LQ_{irt}^{rel} = 2$, $\widetilde{LQ}_{irt}^{rel} = \frac{1}{3}$, whereas $LQ_{irt}^{rel} = \frac{1}{2}$ implies $\widetilde{LQ}_{irt}^{rel} = -\frac{1}{3}$..

11 Related employment includes the employment in related non-traded, public sector and natural-resource-based industries. Moreover, we consider the employment in local establishments of the same industry as related employment. However, excluding this employment does not substantively alter any of our findings.

Regional coherence and structural change

Whereas the resource match is a characteristic of a local industry, i.e., of an industry-region pair, coherence is a regional characteristic. We define coherence as the employment-weighted average resource match of a region's industries:

$$C_{rt} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{irt}^{rel} \qquad \text{(Eq. 5.8)}$$

The coherence tells us how related the industries in a region are to one another. We also calculate how strongly the national industry mix matches the resource base of a given region $\mathbf{r}$:

$$C_{rt}^{base} = \sum_i \frac{E_{i.t}}{E_{..t}} \widetilde{LQ}_{irt}^{rel} \qquad \text{(Eq. 5.9)}$$

where $\frac{E_{i.t}}{E_{..t}}$ is industry $\mathbf{i}$'s share in total national employment. C_{rt}^{base} can be interpreted as a random baseline that tells us the match of the region's industry mix with a fictional region in which each industry's employment is proportional to the national size of the industry. The dynamic counterpart to coherence – structural change – can be measured in much the same way: instead of asking how related a region's industry mix is to the current local economy, we ask how related the industry mix is to the local economy of a base year, $\mathbf{T}$:

$$S_{rt,T} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{irT}^{rel}\text{, where } T < t \qquad \text{(Eq. 5.10)}$$

Structural change by agent type

The regional industry mix changes when local economic agents create or destroy employment. Employment created in local industries with high resource-match values reinforces the focus of that resource base. When agents destroy employment in such industries, central resources are eroded and the resource base's focus shifts. Similarly, for local industries with low resource-match values, employment creation expands the resource base and employment destruction erodes peripheral resources, which tightens the resource base. To study structural change by agent type, we divide all establishments by whether they create or destroy employment. Incumbent establishments are divided into three groups: growing, declining and exiting incumbents. Furthermore, incumbents that switch industries create employment in the industry they enter and destroy employment in the industry they leave.[12] Therefore, we split incumbents that switch industries into two artificial types: "out-switching" incumbents, who destroy employment in the old industry, and "in-switching" incumbents,

12 In principle, firms may also move to another region. However, such events are so rare that we do not explore them further.

who create employment in the new industry. New establishments are split into four groups: new subsidiaries of (1) local firms and (2) non-local firms, and new establishments set up by (3) local and (4) non-local entrepreneurs. Table 5.3 provides an overview of all agent types.

Table 5.3: Agent types

Agent type	Description	ΔE	Effect on resource base if match is below average	above average
incumbent establishments	*existing establishments that ...*			
growing	expand their workforce	+	diversify	specialize
shrinking	reduce their workforce	-	specialize	diversify
closing	close down	-	specialize	diversify
industry switchers	*existing establishments that ...*			
into the industry	switch into the industry	+	diversify	specialize
out of the industry	switch out of the industry	-	specialize	diversify
New establishments	*new establishments set up by ...*			
local expanding firms	pre-existing firm with main employment concentration inside the region	+	diversify	specialize
non-local expanding firms	pre-existing firm with main employment concentration in another region	+	diversify	specialize
local entrepreneurs	new firm created by entrepreneur from inside the region	+	diversify	specialize
non-local entrepreneurs	new firm created by entrepreneur from outside the region	+	diversify	specialize

Column ΔE indicates whether the employment change associated with a given agent type is positive or negative. The final two columns explain the on the regional resource base of a change taking place in industries that are less (column 4) or more (column 5) strongly matched to the region than the average existing local industry in the region.

Appendix 5.B provides a detailed description of how we determine establishment ownership and geographic origins. In short, we first identify new subsidiaries. Establishments that share their firm identifiers with other establishments are classified as subsidiaries. A subsidiary belongs to a local firm if, in the previous year, the parent firm employed most of its employees in the new subsidiary's labor market area, in all other cases, it belongs to a non-local firm. In contrast, if not only the establishment identifier but also the firm identifier is new, we regard the establishment as entrepreneur-owned. Entrepreneurs in such establishments are identified as the workers who draw income from a private business. If the new establishment is located in the same labor market area as the one in which the entrepreneur had been previously employed, its origins are considered local, whereas all others are regarded as non-local. This approach identifies the origins of all new subsidiaries and of some 35,000 out of about 60,000 entrepreneur-owned establishments. Establishments for which the origin could not be determined are hereafter dropped.

The structural change an agent type induces in a region is calculated as the weighted average resource match of all establishments associated with the agent's type to the region's original economic structure, where the weights are given by the employment these establishments create or destroy within a given period of time. That is, the structural change an agent induces between year t and the base year T is defined as:

$$\mathrm{A}^{\mathrm{a}}_{\mathrm{rt,T}} = \sum_{\mathrm{i}} \frac{\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{irt,T}}}{\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{.rt,T}}} \widetilde{\mathrm{LQ}}^{\mathrm{rel}}_{\mathrm{ir,T}} \qquad \text{(Eq. 5.11)}$$

where $\frac{\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{irt,T}}}{\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{.rt,T}}}$ is the employment that the establishments of agent type $\mathbf{a}$ create (or destroy) between the base year T and the current year t in region r and industry i $\left(\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{irt,T}}\right)$ as a share of the total employment created (destroyed) by this agent type in all industries in region $\mathrm{r}\left(\Delta\mathrm{E}^{\mathrm{a}}_{\mathrm{.rt,T}}\right)$. $\mathrm{A}^{\mathrm{a}}_{\mathrm{rt,T}}$ thus shows how strongly an agent type's new (or destroyed) employment is related to the local economy of year T. To facilitate interpretation, we subtract the average match of existing local industries in year T (i.e., we subtract a region's base year coherence):

$$\widetilde{\mathrm{A}}^{\mathrm{a}}_{\mathrm{rt,T}} = \mathrm{A}^{\mathrm{a}}_{\mathrm{rt,T}} - \mathrm{C}_{\mathrm{rT}} \qquad \text{(Eq. 5.12)}$$

Positive values of $\widetilde{\mathrm{A}}^{\mathrm{a}}_{\mathrm{rt,T}}$ now indicate that the agent's activities are more related to the region than the region's pre-existing activities, whereas negative values indicate the agent's activities are less related.

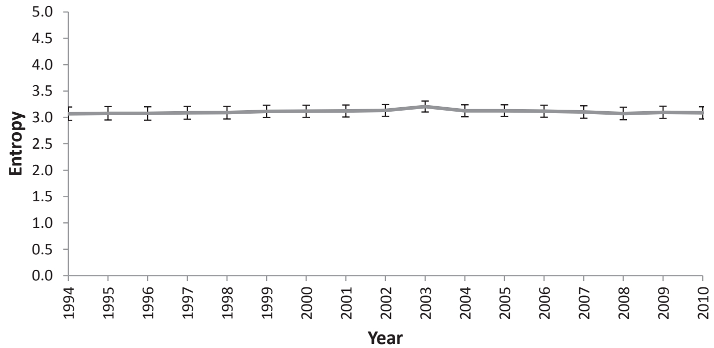
5.4 Results

5.4.1 Diversity and industrial change in Swedish regions

The Swedish regional system features three metropolitan regions (Stockholm, Gothenburg and Malmö), and a range of medium-sized and small regions. The main urban agglomerations are located in mid- and southern Sweden. North of Stockholm, geographical distances between the regional centers are usually vast, and population density low. In recent decades, the metropolitan regions have successfully transitioned to new industries. For instance, Malmö, historically a manufacturing center, suffered strongly when in the 1980s and early 1990s its manufacturing base, and in particular its shipyards, collapsed. However, after Sweden's financial crises of the early 1990s, the city successfully reinvented itself and became host to a number of modern, knowledge-based manufacturing and services activities. In contrast many peripheral and semi-peripheral regions did not recover from their own structural declines (Svensson-Henning 2009; Holm et al. 2013).

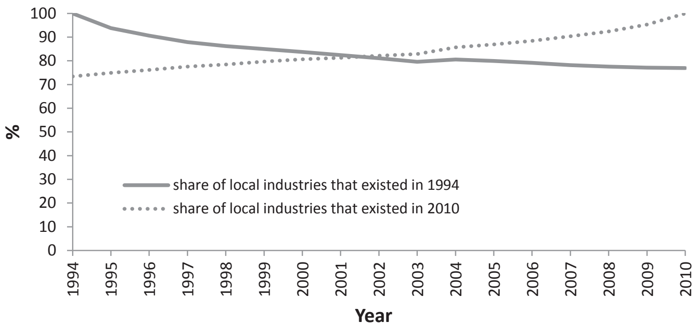
Our analyses start after this period of decline in the manufacturing sector. Figure 5.1 shows how the diversity of Swedish regions has evolved since then. For each year, it depicts the average employment entropy of the regional industry mixes. On average, diversity stays constant throughout the entire time period meaning that Swedish regions have not shown any tendency to become more or less specialized. However, as shown in Figure 5.2, this apparent stability masks significant changes in the industrial composition of these regions: by 2010, 27% of the local industries[13] that existed in 1994 had disappeared and 23% of all local industries in 2010 only appeared after 1994. Moreover, Figure 5.3 shows that this churn of local industries is accompanied by a steady shift away from the 1994 local employment compositions.

Figure 5.1: Average entropy of the employment composition of labor market regions



The figure graphs the average employment entropy of Swedish regions over time. Employment entropy indicates how diversified a local economy is and is calculated as $entropy_{rt} = -\sum_{i=1}^{N} \frac{E_{irt}}{E_{..rt}} \ln \frac{E_{irt}}{E_{..r}}$, where E_{irt} denotes the employment in industry i, region r and year t, and $E_{.rt}$=$\sum_i E_{irt}$. It varies from zero when all employment is concentrated in a single industry, to in N when all local industries have equal employment shares. The error bars depict 95% confidence intervals calculated as ±1.96 times the standard deviation of the entropy's mean across regions.

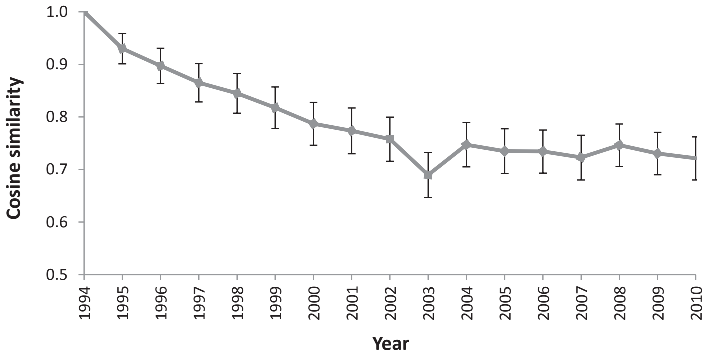
Figure 5.2: Turnover of local industries



The solid line depicts the share of local industries (region-industry combinations) existing *(i.e., with non-zero employment)* in Sweden in 1994, that survived to at least year 1994 + t. The dotted line depicts the share of local industries existing in 2010 that had existed already in year 2010 - t.

13 A local industry is defined as a region-industry combination, such as for instance shipbuilding-in-Gothenburg.

Figure 5.3: Average cosine similarity to the base year 1994 of regional employment profiles



The graph depicts the average cosine similarity between a region's current industrial employment mix and the industrial employment mix of the base year 1994. The cosine similarity measures the similarity of two vectors, i.e., the region's employment profile at two different points in time: $cos\_sim_{rt,T} = \frac{e_{rt} \cdot e_{rT}}{\sqrt{|e_{rt}||e_{rT}|}}$, where $e_{rt} = (E_{1rt} \ldots E_{Nrt})'$ a vector whose elements correspond to region r's employment in industry i in year t. The cosine distance ranges from -1 (opposite profiles) through 0 (unrelated profiles) to +1 (same profile). The error bars depict 95% confidence intervals calculated as ±1.96 times the standard deviation of the mean of the cosine similarity across regions.

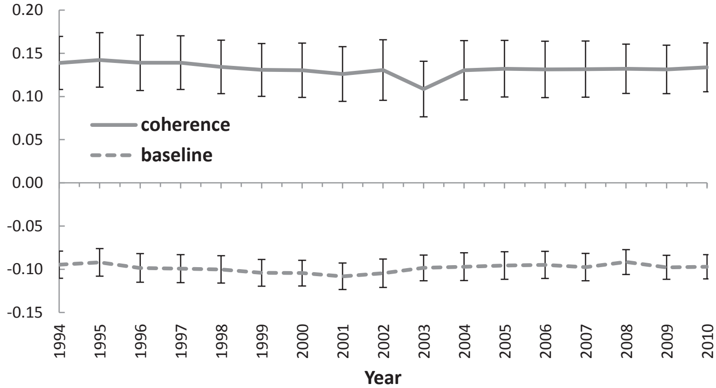
5.4.2 Coherence and structural change

So far we have ignored the fact that different industries can use similar resources and that changes in industry composition may be quite superficial, with little consequence for the region's resource base. Figure 5.4 therefore shows the average coherence of regions and how it evolves. The average regional coherence exceeds its baseline significantly in every single year. Local industries are thus more closely related to each other than to the Swedish economy as a whole. This suggests that the different industries in a region share a relatively narrow set of regional resources, just like a firm's product portfolio is often organized around some core competences.

There is little evidence that these regional resource bases change much over time. In spite of the significant entry and exit of local industries, Figure 5.4 shows that the coherence of regions hardly changes, with none of the mild fluctuations being statistically significant. Moreover, the downward-sloping line in Figure 5.5 implies that, although local economies drift away from their original resource bases, this process unfolds very slowly. The point estimate of the slope in Figure 5.5 of -0.0029 (t-statistic: -3.76) implies that it takes the average region over 50 years to move one standard deviation away from its base-year position. Another way to put this is that it would take the average region over 50 years to converge to the industrial structure of the national economy.[14]

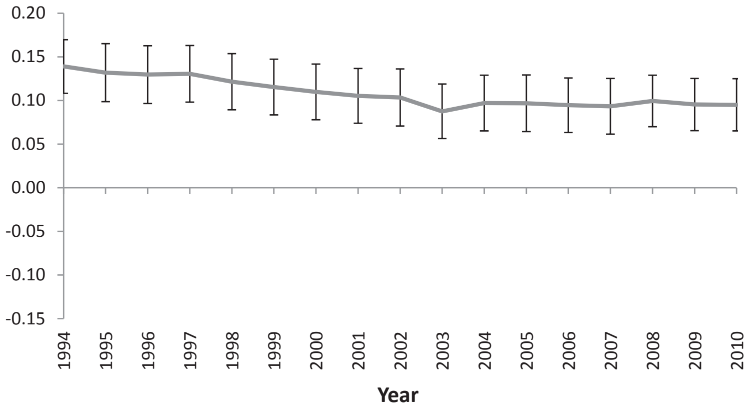
14 The distance between the average region and the national economy in terms of industrial structure is slightly over one standard deviation.

Figure 5.4: Coherence of labor market regions' resource bases



The upper line depicts the average coherence of a regions' resource base as measured by its local industries' employment-weighted average resource match to the regional economy as a whole $(C_{rt} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{irt}^{rel})$. As a baseline, the lower line depicts the development of the average resource match of Sweden's aggregate, national industries to the region's resource base $(C_{rt}^{base} = \sum_i \frac{E_{i.t}}{E_{..t}} \widetilde{LQ}_{irt}^{rel})$. The error bars depict 95% confidence intervals calculated as ±1.96 times standard deviation of the mean across regions.

Figure 5.5: Structural change in Sweden's labor market regions



The graph depicts the average resource match of a regions' local industries to the local economy of the base year 1994 $(S_{rt,1994} = \sum_i \frac{E_{irt}}{E_{.rt}} \widetilde{LQ}_{ir1994}^{rel})$, including 95% error bars. A downward trend signals diversification, an upward trend a tightening of the existing focus. Error bars depict 95% confidence intervals calculated as ±1.96 times the standard deviation of the mean structural change across regions.

As we noted before, structural change is not necessarily positive for individual regions. In some regions, structural change means that they acquire new resources that allow them to grow richer, but in other regions structural change reflects the erosion of valuable resources. To illustrate this, we calculate the change of the average Mincer residual (Mincer 1974) in a region's export industries between 1994 and 2010. This residual is constructed by regressing workers' log-transformed wages on their gender, age, age-squared and their educational attainment. It tells us how much more workers earn than we would expect given their age and education. Therefore, we interpret this as a proxy for the region's labor productivity.

The scatter diagram in Figure 5.6 shows that there is no obvious relation between structural change and changes in Mincer residuals. Indeed, each quadrant (defined by sample medians) contains a substantial number of regions. In the lower left quadrant, we find regions that became more focused, but lost productivity. These are typically rather small and peripherally located Northern regions. In contrast, the three metropolitan regions of Stockholm, Gothenburg and Malmö, are all found in the upper-left quadrant where an increased focus was accompanied by productivity increases. Indeed, contrary to what could perhaps be expected, the success of these regions since the mid-1990s seems not driven by an increase in diversity, but by a deepening focus on sets of related industries. In the two right-most quadrants, we find regions that underwent structural change.

Regions that underwent structural change are found in the right part of the scatter diagram. Here, we find several small-scale entrepreneurial regions in the south of Sweden such as Markaryd, Gnosjö and Värnamo, all consistently ranked among the top 30 most entrepreneurial municipalities by the Confederation of Swedish Enterprise[15]. However, structural change was accompanied by very different productivity dynamics in these regions. For instance, in Markaryd (in the upper-right quadrant) structural change meant an expansion and increase in productivity of its traditionally strong machinery sector. In Gnosjö (found in the lower-right quadrant) structural change was much less benign. This city saw its manufacturing base erode and lose productivity. In neighboring Gislaved, a municipality of about 30,000 inhabitants, structural change culminated in the job loss of around 750 people in the closure of a tire factory in 2002.

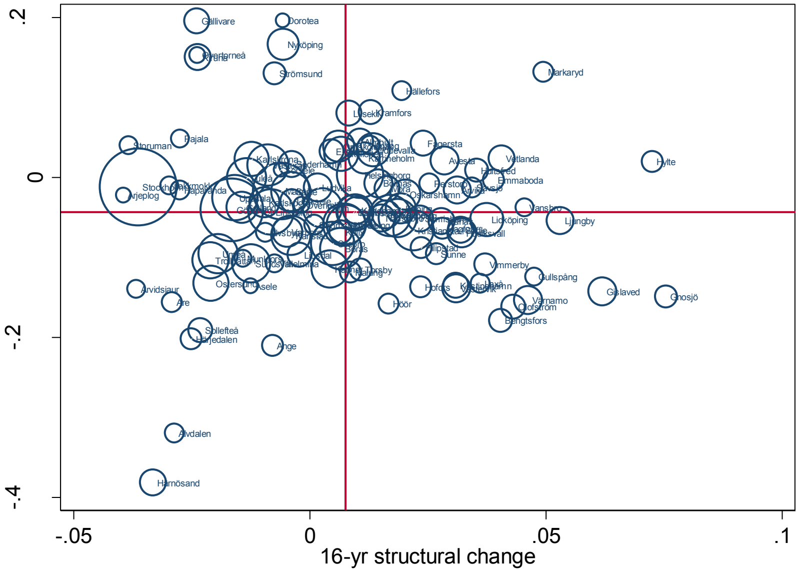
Apparently, structural change is not always a positive phenomenon. Indeed, it can be a symptom of decline as well as of renewal. This is even more evident when comparing the development of productivity growth and structural change over time for the examples of Markaryd, where structural change and productivity move in tandem, and Gnosjö, where they move in opposite directions (Figures 5.7a and 5.7b). However, as argued by, among others, Jacobs (1969), Grabher (1993) and Glaeser (2005), and as Malmö's restructuring in the 1980s and 1990s shows, in the long run, structural change is all too often inevitable.

5.4.3 Agents of structural change

Who is most involved in this structural change? Table 5.4 summarizes the number of establishments and employment by decomposing the employment created or destroyed in local industries by establishment type. For new establishments, we aggregate all that enter between 1994 and 2000 and analyze the employment they create in the first and in ten years after they were created. Establishments that switch industries are treated analogously. Between 1994 and 2000, new establishment creation accounted for about 17,000 jobs a year. In contrast, growing incumbents created about 76,000 jobs in one year (i.e., from 1994 to

15 www.foretagsklimat.se

Figure 5.6: Structural change and productivity (1994-2010)



Scatter diagram of the change in average Mincer residual in the export industries of a region against the structural change the region underwent in the period 1994-2010. Markers are scaled by the total size of a region's workforce in 1994.

Figure 5.7a: Structural change and productivity in Markaryd

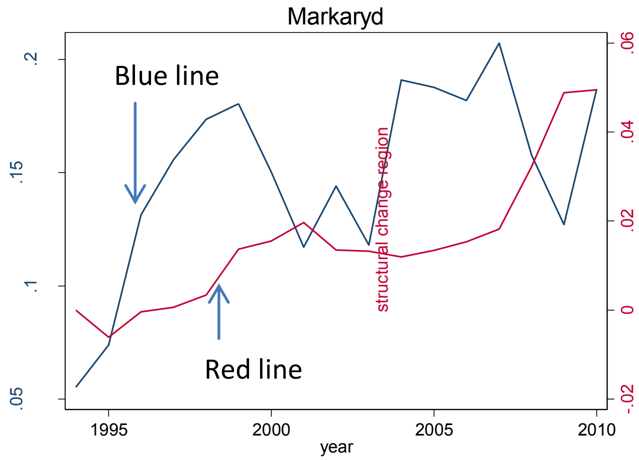
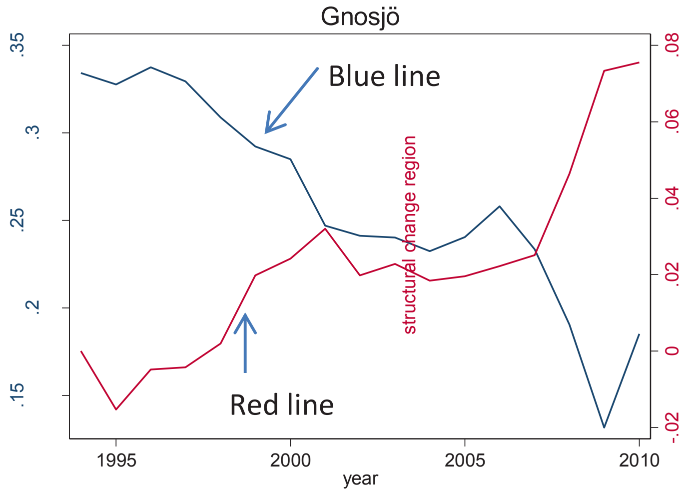


Figure 5.7b: Structural change and productivity Gnosjö



Structural change in Markaryd (Figure 5.7a) and Gnösjö (Figure 5.7b) vis-à-vis the base year 1994 (red line) and regional productivity in export industries as proxied by the average wage residual in export industries (blue line).

1995). Some of the new establishments introduced new industries to their regions, but the frequency with which this happened differs markedly by agent type. For instance, 4% of new subsidiaries of existing firms created new local industries against about 2% for entrepreneur-owned establishments. However, much of this difference can be attributed to the fact that new subsidiaries often have non-local owners. Indeed, local-industry formation rates are very similar, at around 2%, for local firms and local entrepreneurs, but they are much lower than the 4.8% for new subsidiaries of non-local firms and the 4.2% for establishments of non-local entrepreneurs. By and large, these results foreshadow our findings on structural change, which take into account that some new industries represent bigger shifts in the underlying resource base than others.

Short-term structural change

Figure 5.8 summarizes the amount of structural change within a one-year time period that the employment shifts associated with each agent imply.[16] Agent types are listed along the horizontal axis. The associated average resource-match to their regions (the agents' $\widetilde{\mathrm{A}}^{\mathbf{a}}_{\mathbf{rt,T}}$ values) are plotted on the vertical axis. To facilitate interpretation, the $\widetilde{\mathrm{A}}^{\mathbf{a}}_{\mathbf{rt,T}}$-axis is also expressed on a secondary (right-hand) axis in percentiles of the overall match distribution of existing local industries in 1994. For instance, $\widetilde{\mathrm{A}} = \mathbf{-0.10}$ corresponds roughly to the 23rd match-percentile. This means that only 23% of all existing employment in 1994 was less well-

16 Incumbents are defined as establishments that exist in the base year, 1994. However, to increase the sample of agents that set up new establishments, we take all new establishments between 1994 and 2000. Next, we record the structural change induced one year after they were founded. That is, for new establishments, we pool $\tilde{A}^{a}_{r94,95}$, $\tilde{A}^{a}_{r95,96}$, $\tilde{A}^{a}_{r96,97}$, $\tilde{A}^{a}_{r97,98}$, $\tilde{A}^{a}_{r98,99}$, and $\tilde{A}^{a}_{r99,00}$

Table 5.4: Agent types: employment, number of establishments and new local industries

Agent type	# establishments			employment		% creating new local industries
	entry yr	after 1 yr	after 10 yrs	after 1 yr	after 10 yrs	
Growth, decline and exit						
Incumbent growth		17507	9933	75851	122359	
Incumbent decline		12494	8031	46577	77776	
Incumbent exit		10420	45268	29794	270030	
Industry switching						
Entered industry		1708	3643	32629	107652	
Exited industry		1708	3643	30812	93492	
New establishments						
All expanding firms	2249	1809	666	38419	21449	4.09%
All entrepreneurs	51806	35307	10206	63166	37992	2.38%
Local expanding firms	557	435	152	13263	7562	1.97%
Non-local expanding firms	1692	1374	514	25156	13887	4.79%
Local entrepreneurs	42993	29617	8644	53741	32798	2.01%
Non-local entrepreneurs	8813	5690	1562	9425	5194	4.20%

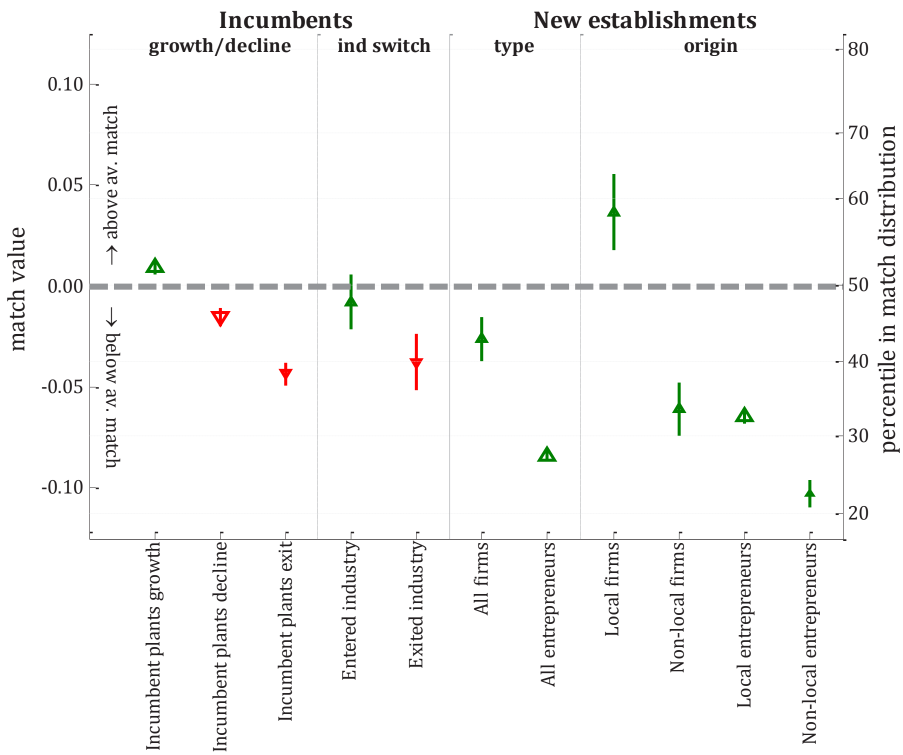
New establishments and industry switching establishments and their employees refer to the sum over establishments that were founded or switched industries in the six years between 1994 and 2000. Incumbents are establishments that existed already in 1994.

matched than the local industries in which this employment has been created (or destroyed). Agent types are classified by those that generate employment (depicted by upward-pointing arrows) and those that destroy employment (down-ward pointing arrows). The arrow sizes vary with the total employment an agent represents. Positive values of $\tilde{A}$ indicate that an agent type is generally found in local industries that match the region better than the existing employment does. Negative values of $\tilde{A}$ correspond to industries with below-average match values.

Figure 5.8 shows that agents change their regions in different ways. Incumbent establishments tend to reinforce current specializations. If they grow, they do so predominantly in above-averagely matched industries. If they shrink or close down, they tend to reduce employment in below-averagely matched industries. Moreover, incumbents that switch industries tend to move to industries that fit the region better: on average, they abandon industries in the 40th and enter industries in the 47th match-percentile.

In contrast, new establishments tend to diversify a region's resource base. Indeed, in support of Hypothesis 1 (incumbents induce less structural change than new establishments), almost all new-establishment types display below-average $\tilde{A}$-values. The only exception are local firms' new subsidiaries, which are mostly found in industries closely matched to

Figure 5.8: Structural change by agent type over a 1-year horizon



Markers show by how much an agent's average resource match exceeds the average resource match of existing local industries after 1 year. Employment created (destroyed) at $\tilde{A} > 0$ corresponds to diversification (further focusing) of the regional resource base. Employment-creating agents are denoted with, upward pointing arrows, employment-destroying agents with downward-pointing arrows. Error bars depict 95% confidence intervals, based on the standard deviation of the mean resource match across all establishments of an agent type. To facilitate interpretation of $\tilde{A}$-values, the second vertical axis provides the percentiles a match value corresponds to in the distribution of 1994 match values.

the region's industry mix. However, such subsidiaries simply represent incumbent growth accommodated in new facilities. Although strictly speaking in contradiction to Hypothesis 1, it is therefore not surprising to find these establishments to behave like growing incumbents and to increase a region's focus.

All other new establishments induce structural change, but they do so to different extents. For instance, new subsidiaries of existing firms tend to be found in more strongly matched industries (42nd match-percentile), than those of entrepreneurs (29th match-percentile). This supports Hypothesis 3b over Hypothesis 3a: entrepreneurs induce more structural change than expanding firms. Furthermore, establishments that come from outside the region induce much more structural change than those that originate from within the region. On average, local entrepreneurs create employment in the 32nd match-percentile, against the 22nd for non-local entrepreneurs, which is both statistically and economically significant. The difference between new subsidiaries of local (59th match-percentile) and non-local (33rd) firms is even larger. This finding supports Hypothesis 2 (non-local agents induce more structural change than local agents).

Our findings are closely related to those in Dumais et al. (2002) work on changes in industries' spatial concentration. Consistent with our finding that new establishments induce structural change, these authors show that new establishments have a deagglomerating effect on industries. Furthermore, they find that exits lead to a strengthening of existing agglomeration patterns in the same way that we report exits to reinforce existing capability structures. However, the fact that incumbent growth and decline weaken an industry's spatial concentration, contrasts with our result that they strengthen existing specializations.

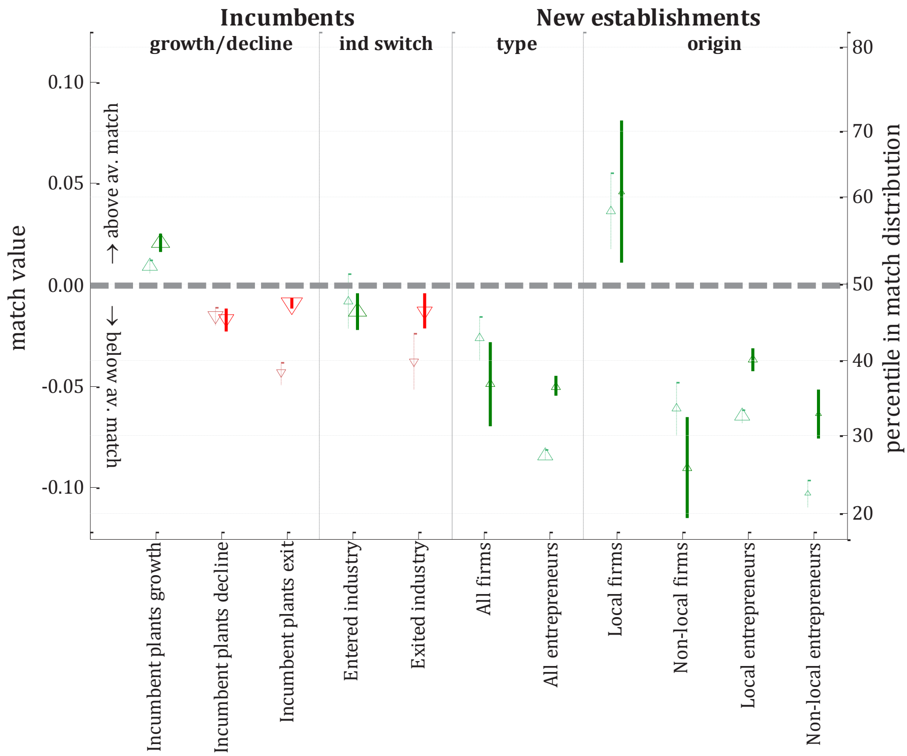
Long–term structural change

So far, we find that new establishments of non-local entrepreneurs change a regional resource base the most, followed by those of non-local firms. However, structural change is typically associated with a much longer time horizon than the one-year changes depicted in Figure 5.8. To induce long-lasting structural change, it is not enough that establishments in unrelated industries are created, they also need to survive and grow. Therefore, Figure 5.9 repeats the analyses of Figure 5.8 for a 10-year period, while plotting the 1-year results as a reference.

Comparing structural change across a span of ten years to that of a 1-year period, we find that change is typically attenuated (almost all arrows move up). This means that establishments grow faster and/or survive longer in local industries that are better matched to their regional economies, confirming existing studies showing that firms benefit from nearby related economic activity (Delgado et al., 2010; Neffke et al., 2012). Indeed, the fact that match values for out-switching and exiting incumbents shift up (i.e., occur at higher match values) confirms that unrelated activities are abandoned through establishment closures and adjustments in industry orientation.

Apart from this general attenuation, long-term structural-change patterns are similar to short-term ones. On a ten-year horizon, incumbents (weakly) reinforce a region's focus, whereas new establishments mostly create employment in unrelated industries. Among these new establishments, entrepreneur-owned establishments' $\widetilde{A}$-values shift upward, implying that their growth and/or survival are concentrated in higher-matched industries. In contrast, the new subsidiaries of existing firms either remain at the same match-value (local firms) or even move down (non-local firms). Apparently, unlike the new establishments of entrepreneurs, subsidiaries of non-local firms grow more and/or survive longer in low-match industries. As a result, non-local firms just surpass (although not to a statistically significant extent) entrepreneurs as the main agents of structural change.

Figure 5.9: Structural change by agent type over a 10-year horizon



Markers show by how much an agent's average resource match exceeds the average resource match of existing local industries after 10 years. Employment created (destroyed) at $\tilde{A} > 0$ corresponds to diversification (further focusing) of the regional resource base. Employment-creating agents are denoted with green, upward pointing arrows, employment-destroying agents with red downward-pointing arrows. Error bars depict 95% confidence intervals, based on the standard deviation of the mean resource match across all establishments of an agent type. To facilitate interpretation of $\tilde{A}$-values, the second vertical axis provides the percentiles a match value corresponds to in the distribution of 1994 match values.

Plant survival

As noted above, new establishments can only create structural change if they manage to survive in the absence of related industries. Therefore, we take a closer look at the extent to which different agent types depend on the presence of related industries. In particular, we estimate linear probability models for the event that a new establishment survives for at least 10 years. As explanatory variables, we use dummies for agent types and interact them with the natural logarithm of related employment in the region.[17] We also include entry-year, region and industry dummies as control variables. However, because we are interested in how survival rates differ by agent type, not necessarily in why they do so, we do not control

17 In regression analyses, a coefficient for log-transformed employment figures is easier to interpret than a coefficient for the match variable, which is normalized against industry and region size. Instead we rely on industry and region fixed effects to absorb any idiosyncrasies at the industry or regional level.

for any other establishment characteristics, such as start-up size. Table 5.5 summarizes the results.

On average 20.1% of new establishments survive for at least 10 years. Column (1) of Table 5.5 shows that establishments of non-local founders have a 2.1 percentage-point lower survival rate than those of local founders. The model in column (2) interacts the local-founder-dummy with the amount of related employment in a region. It shows that plants that enter regions where much related employment is found tend to survive longer, especially if their founders are local.[18] The estimated coefficients suggest that doubling the related employment translates into a 1.2 percentage-point increase in survival rates for local establishments and a 0.9 percentage-point increase for non-local establishments.[19] Even larger differences emerge when we split founders into entrepreneurs and existing firms (columns (3) and (4)). Whereas firm-owned subsidiaries exhibit higher survival rates than entrepreneur-owned establishments, only entrepreneur-owned establishments are sensitive to the amount of related employment in the region. Column (5) further subdivides establishments by their geographical origin. Regardless of whether an establishment was founded by local or non-local entrepreneurs, survival rates of entrepreneur-owned establishments are always lower than those of firm subsidiaries. However, whereas local roots are associated with higher survival rates among entrepreneurs (the omitted category is local entrepreneurs), the opposite holds for firm-owned subsidiaries: here, non-local origins are associated with higher survival rates. Furthermore, Column (6) again suggests that related employment in the region only matters for entrepreneur-owned, not for firm-owned establishments.[20]

These findings are consistent with the theoretical framework of section 5.2. Firstly, that only entrepreneur-owned establishments depend on the local availability of related employment for their survival (column 4) is in line with the notion that entrepreneurs depend more strongly on local resources than subsidiaries of larger firms. Secondly, the hypothesis that entrepreneurs cannot draw on a parent firm to compensate for outsiders' lack of access to local resources explains why we find higher failure rates for non-local entrepreneurs but not for non-local firms in column (5). However, such a causal interpretation is hazardous, because the decision to enter a region is endogenous, even conditional on industry and region fixed effects. For instance, the fact that firm-owned subsidiaries seem unaffected by the presence of related employment could also mean that they are more careful when choosing a location and, consequently, make fewer mistakes (or take less risk) when deciding where to locate.

Aggregate structural change

So far, we have determined the average intensity, not the amount of structural change agents induce. However, not all agents are equally prevalent: new establishments of local

18 A t-test reveals that this difference is statistically significant at a p-value of 0.026.

19 The effect size of raising related employment by a factor ξ is calculated as: $\times \ln(\xi)$.

20 Although the effect of $\ln(\text{rel. emp.})$ differs between local and non-local entrepreneurs, this difference is not statistically significant (*i.e.*, the difference of the interaction with $\ln(\text{rel. emp.})$ is statistically insignificant).

Table 5.5: Establishments' 10-year survival rates *(Dep. var.: ≥10 yr survival (0/1))*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Non-local agent	-0.021*** (0.004)	0.02 (0.018)				
Firm agent			0.073*** (0.009)	0.209*** (0.047)		
Local firm					0.041** (0.016)	0.148 (0.094)
Non-local firm					0.074*** (0.01)	0.191*** (0.056)
Non-local entrepreneur					-0.037*** (0.004)	-0.009 (0.019)
Local X ln(rel. emp.)		0.017*** (0.005)				
Non-local X ln(rel. emp.)		0.013*** (0.005)				
Firm X ln(rel. emp.)				0.004 (0.007)		
Entrepreneur X ln(rel. emp.)				0.017*** (0.005)		
Local Firm X ln(rel. emp.)						0.006 (0.01)
Non-local firm X ln(rel. emp.)						0.004 (0.007)
Local entrepr. X ln(rel. emp.)						0.017*** (0.005)
Non-local entrepr. X ln(rel. emp.)						0.014*** (0.005)
Constant	0.157*** (0.005)	-0.053 (0.057)	0.153*** (0.005)	-0.057 (0.057)	0.156*** (0.005)	-0.042 (0.057)
Entry-year FEs included?	yes	yes	yes	yes	yes	yes
Industry FEs included?	yes	yes	yes	yes	yes	yes
Region FEs included?	yes	yes	yes	yes	yes	yes
Observations	54055	54055	54055	54055	54055	54055
R-square	0.0254	0.0257	0.0265	0.0270	0.0280	0.0284

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses
Linear probability models of 10-year survival rates for new establishments that enter the Swedish economy in traded, private sector, non-resource based industries between 1994 and 2000. The unconditional average 10-year survival rate for the establishments in the sample is 0.201.

entrepreneurs outnumber those of non-local entrepreneurs 5-to-1 and those of non-local firms 20-to-1. Therefore, although they may move a region's resource base less individually, all local entrepreneurs together could still produce much structural change. To determine how much structural change agents produce as a group, we analyze how much of the expansion in the most unrelated industries can be attributed to each agent type. In particular we study the new-establishment employment that was created over a ten-year period in the bottom 5th match percentile, which represents the most unrelated local industries in a region. We find that non-local firms create about 23% of all new-establishment employment and account for 27% of the new employment in the 5th match percentile. More strikingly, non-local entrepreneurs produce 29% of new-establishment employment in the 5th match percentile, even though they create just 9% of the total new-establishment employment. Taken together, new establishments with non-local origins create 56% of such unrelated new-establishment employment, even though they represent just a third of all new-establishment employment. This once more shows that non-local agents are key actors in regional structural change.

Spatial diffusion through the mobility of firms and entrepreneurs

The finding that non-local agents renew the resource base of a region suggests that non-local agents help industries and the resources they require diffuse. If this is true, even though the activities of non-local agents are typically quite unrelated to their host regions' industry mix, they should be strongly related to the industry mix of their home regions. Table 5.6 shows that this is indeed the case: for entrepreneurs, and even more so for firms, from outside the region, the resource match to their home regions is much higher than the resource match to their host regions. This implies that the mobility of firms and entrepreneurs is an important vehicle for the diffusion of resources across regions.

Table 5.6: Average resource match of non-local agents to home and host region

Agent type	**Resource match to:**		**p-value**
	home region	**host region**	
Non-local expanding firms	0.072 (0.004)	-0.019 (0.004)	0.000
Non-local entrepreneurs	0.001 (0.002)	-0.019 (0.002)	0.000

Average resource match of a non-local agent to home and host region (standard error in parentheses). Home region is defined as the region in which the new establishment's parent firm employed most of its workers (non-local firms) or in which the new establishment's entrepreneur was employed in the year prior to opening the new establishment (non-local entrepreneurs). p-value refers to a test of equal means for the agent's resource match to the home versus to the host region.

5.5 Conclusion

5.5.1 Summary

There are many parallels between the RBVs depiction of firm growth and the way in which regional economies develop. In firms as well as in regions, growth does not just involve enlarging the scale but also the scope of production. Moreover, for both firms and regions, this expansion of scope is predominantly achieved through related diversification. However, whereas firms can exclude others from their resources, access to regional resources is less restricted. Still, economic agents differ in their reliance on, and access to, regional resources. For instance, subsidiaries can substitute their parents' resources for regional resources whereas entrepreneurial ventures cannot, and local firms and entrepreneurs are often better positioned to access local resources than their counterparts from outside the region. As a consequence, agents differ in the extent to which they will use (and therewith change) the resource base of a region.

Set against this framework, we studied which agents shift employment to unrelated industries and thereby induce structural change. We find that, unlike the relatively fast change of a region's industry mix, structural change is unfolds much more slowly. Moreover, whereas incumbents tend to deepen a region's resource base, most new establishments shift the region's resource base by creating employment in unrelated industries. Among the new establishments, entrepreneur-owned establishments create most structural change in the short run but they are less capable of sustaining employment in unrelated industries than subsidiaries of non-local firms. Consequently the latter become marginally more important agents of change in the long run. Overall however, most structural change is brought by agents from outside the region. It is the mobility of these entrepreneurs and firms that fuels the diffusion of industries and helps regions diversify. Although the results are based on skill relatedness to measure related employment, our conclusions prove robust when using other relatedness measures.[21]

5.5.2 Discussion

The fact that regions' industry mixes fluctuate strongly, while their underlying resource bases change much more slowly highlights that the current constellation of industries in a region is just one manifestation of how existing local resources can be put to work. This speaks to the discussion on regional renewal, a topic that ranks highly on the agenda of local policy makers. For instance, in the American context, cities like Detroit and Pittsburg are prime examples of urban economies that at some point ran into the limits of their economic specializations. In Europe, regional renewal and transformation are important goals of the European Union's (EU) smart specialization agenda. Such policy frameworks typically place high expectations on entrepreneurs to discover which new activities are feasible in a region (Hausmann and Rodrik, 2003; Foray and Goenaga, 2013; McCann and Ortega-Argilés, 2015). However, our results question the canonical image of the heroic Schumpeterian entrepreneur as the prime transformative force in local economies. Although there undoubtedly are local entrepreneurs who shake up the regional status quo, we found them to be rather the exception.

As a consequence, transformation policies that rely wholly on a local entrepreneurial discovery processes are not without risks. Indeed, a more important factor in structural change than Silicon-Valley-style homegrown entrepreneurship seems to be mobility: unrelated activities are typically transferred from elsewhere by entrepreneurs and firms from outside the region.

5.5.3 Caveats and future research

We infer the extent of structural change from the degree to which a region's industries becomes less related to the region's initial mix of industries. Because inter-industry

21 See Appendix 5.C, where all reported findings are replicated using relatedness indices based on the industry classification system and on input-output linkages.

relatedness is commonly held to reflect relatedness in resource requirements (e.g., Teece et al., 1994; Farjoun, 1994; Bryce and Winter, 2009), shifts into unrelated industries represent shifts in the underlying resource base. The advantage of this approach is that it allows measuring structural change in a unified way across different regions and agents. However, a clear limitation is that resources are not directly observed but used as a latent. It would be interesting to compare the results of our approach with those of a more detailed analysis of the institutional and economic layout of regions.

Secondly, our analyses answer the question of who introduces unrelated economic activities in a region. In essence, this question is descriptive, not causal: we intend to decompose structural change by agent type, not explain its causes. We therefore remain agnostic about whether the reported differences among agent types reflect different intrinsic capacities for structural change or, for instance, differences in location choices. Similarly, in the survival analyses, we cannot distinguish spatial sorting of establishments from agglomeration externalities, an issue that has attracted considerable attention in urban economics (e.g., Combes et al., 2008).

A third limitation of our study is that we focus on firms and entrepreneurs as the only agents of change. Although firms will ultimately implement structural change in a regional economy, there is increasing interest for how local agents (private and public) engage in collective action to mobilize knowledge, resources and public opinion to create new or adapt existing institutions to enable new industry formation, and the key role that both regional and national stakeholders and governments can play (Strambach 2010; Sotarauta and Pulkkinen 2011).

A fourth caveat is that, by focusing on the new establishments that enter an economy, we have highlighted the diversification aspect of structural change. However, there are well-known examples in which structural change takes the shape of the collapse of a region's core industry and a concurrent erosion of local resources (e.g., Grabher, 1993). Indeed, although leveraging existing resources is often attractive in the short run, in the long run, regions will have to adapt to new economic realities. The optimal balance of related and unrelated diversification – and hence, the optimal speed of structural change – is an important topic, but left for future research.

Our study also raises a number of new questions. For instance, the fact that firms switch industry affiliations from low-match to high-match industries suggests that firm strategies interact with regionally available resources in ways that are still poorly understood. Furthermore, our analyses focused on regions in Sweden, a wealthy, industrialized nation, in a period of relatively steady growth. It would be interesting to know whether our results can be generalized to other contexts where structural change is both more prevalent and pressing. For instance, how does structural change progress in emerging economies? And who introduces structural change in periods where the leading techno-economic paradigms (Freeman and Perez, 1988) are running out of steam? These are important questions and we hope that our framework will prove useful in answering them.

Appendix 5.A: Classification of industries

Table 5.7: Industries included in the analyses

Industry codes	Description	Definition industry	Included
0000 - 1499	Agriculture, hunting and forestry + Fishing + Mining and quarrying	Traded, resource-based	no
1500 - 3999	Manufacturing	Traded, not resource-based	yes
4000 - 4999	Electricity, gas and water supply + Construction	Non-traded	no
5000 - 5199	Wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods	Non-traded	no
5200 - 5299	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	Non-traded	no
5500 - 5599	Hotels and restaurants	Non-traded	no
6000 - 6420	Transport, storage and communication	Non-traded	no
6500 - 6999	Financial intermediation, except insurance and pension funding	Traded, not resource-based	yes
7000 - 7199	Real estate + Renting activities	Non-traded	no
7200 - 7399	Computer and related activities + Research and development	Traded, not resource-based	yes
7400 - 7499	Other business activities	Traded, not resource-based	yes
7500 - 7599	Public administration and defense, compulsory social security	public sector	no
7600 - 8599	Education, Health and social work	public sector	no
8600 - 9999	Other community, social and personal service activities + Activities of households + Extra-territorial organizations and bodies	public sector	no

Appendix 5.B: Determining the founders and geographical origins of new establishments

To identify the origins of each establishment, we first determine whether a new establishment is an entrepreneurial entry or an entry by an existing firm. Every establishment has a unique establishment identifier and a firm identifier (see Andersson and Arvidsson, 2006), which enables us to follow establishments over time regardless of changes in ownership or legal status. Entrepreneurial entries are new establishments that create new firms (i.e., both the establishment and the firm identifiers did not exist before year t). New establishments of existing firms arise when the establishment identifier is new in year t but the establishment's firm identifier already existed in year $t-1$.

Geographical origins of new establishments are determined as follows. For every new establishment of pre-existing firms, the origin is the region where the parent firm employed most of its workers in the year prior to the new establishment's creation. To identify the origins of entrepreneurial entries, we take a number of steps. Firstly, Statistics Sweden supplies information on workers who derive income from a private venture, which we use as an indicator of entrepreneurship. If there is only one entrepreneur in the new establishment, we take that person as the establishment's entrepreneur. The region where he or she was employed in the previous year is now used as the geographical origin of the new establishment. If a new establishment employs multiple entrepreneurs, and if all these entrepreneurs used to work in the same region, we take this region as the geographical origin. If no entrepreneur is found but the new establishment has only one employee, we assume this is the founder and we take the region in which that person worked in the previous year as geographical origin. If no entrepreneur is found and if the new establishment has multiple employees, and if all these entrepreneurs worked in the same region the year before, we take this region as the establishment's geographical origin. This way, we were able to trace the origins of 35,000 new establishments that did not belong to pre-existing firms. All other new establishments were dropped from the analyses.

Appendix 5.C: Alternative relatedness measures

We repeated all analyses reported in the main text with two alternative relatedness indicators. The first is based on the industry classification system (*NACE-relatedness*). The second relatedness index is based on input-output relations among industries. Below we describe how each relatedness measure is constructed and then replicate Figures 5.4, 5.5 and 5.9 and Tables 5.5 and 5.6 based on the described index.

Industry–classification–based relatedness (NACE)

To measure NACE-relatedness, we classify the 4-digit industries in the European NACE classification as related when they belong to the same 2-digit sector. For instance, 'Manufacture of cast iron tubes' (industry code 2721) and 'Manufacture of steel tubes' (industry code 2722) are related because they belong to the same 2-digit sector 27 'Manufacture of basic metals'. The corresponding tables and graphs are shown below.

Table 5.8: Average resource match of non-local agents to home and host region (NACE-relatedness)

Agent type	Resource match to:		p-value
	home region	host region	
Non-local expanding firms	0.113 (0.007)	-0.089 (0.007)	0.000
Non-local entrepreneurs	-0.043 (0.003)	-0.081 (0.003)	0.000

See Table 5.6

Table 5.9: Establishments' 10-year survival rates (NACE-relatedness), *Dep. var.: ≥10 yr survival (0/1)*

	(1)	(2)	(3)	(4)	(5)	(6)
Non-local agent	-0.021*** (0.004)	0.015 (0.013)				
Firm agent			0.073*** (0.009)	0.179*** (0.034)		
Local firm					0.041** (0.016)	0.109 (0.075)
Non-local firm					0.074*** (0.01)	0.170*** (0.039)
Non-local entrepreneur					-0.037*** (0.004)	-0.016 (0.013)
Local X ln(rel. emp.)		0.007*** (0.003)				
Non-local X ln(rel. emp.)		0.002 (0.003)				
Firm X ln(rel. emp.)				-0.007 (0.005)		
Entrepreneur X ln(rel. emp.)				0.007*** (0.003)		
Local Firm X ln(rel. emp.)						-0.002 (0.009)
Non-local firm X ln(rel. emp.)						-0.006 (0.005)
Local entrepr. X ln(rel. emp.)						0.006** (0.003)
Non-local entrepr. X ln(rel. emp.)						0.004 (0.003)
Constant	0.157*** (0.005)	0.088*** (0.027)	0.153*** (0.005)	0.085*** (0.027)	0.156*** (0.005)	0.09*** (0.027)
Entry-year Fes	yes	yes	yes	yes	yes	yes
Industry Fes	yes	yes	yes	yes	yes	yes
Region Fes	yes	yes	yes	yes	yes	yes
Number of observations	54055	54055	54055	54055	54055	54055
R^2	0.0254	0.0257	0.0265	0.0269	0.0280	0.0283

See Table 5.5.

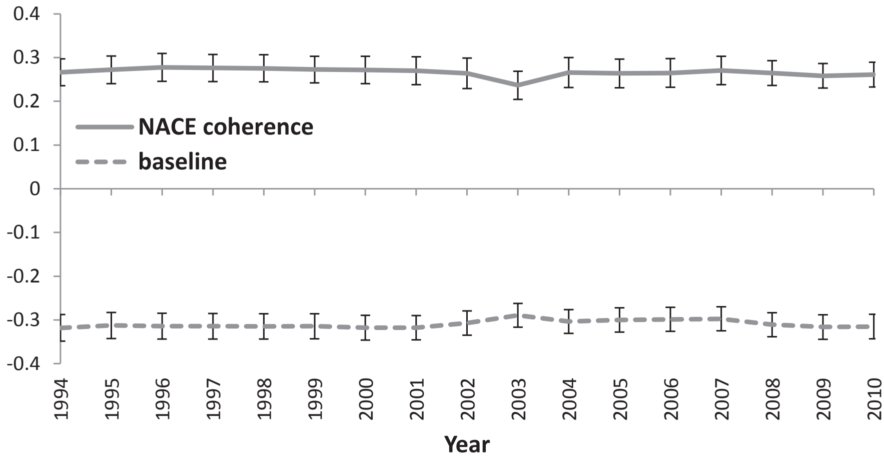
Input–output relatedness

Input-output linkages are derived from the Swedish input-output table of 1995, which is available from Statistics Sweden. For every pair of industries, (i, j), we calculate the share of industry i's inputs that are sourced from industry j and the share of industry i's output that is consumed by industry j. We then average both numbers to arrive at a measure of input-output relatedness between the two industries. If CF_{ij} represents the value of the commodity flow of industry i to industry j, then the input-output relatedness between industries i and j, IOR_{ij}, is given by:

$$IOR_{ij} = \frac{1}{2}\left(\frac{CF_{ij}}{\sum_k CF_{ik}} + \frac{CF_{ji}}{\sum_l CF_{li}}\right) \quad \text{(C1)}$$

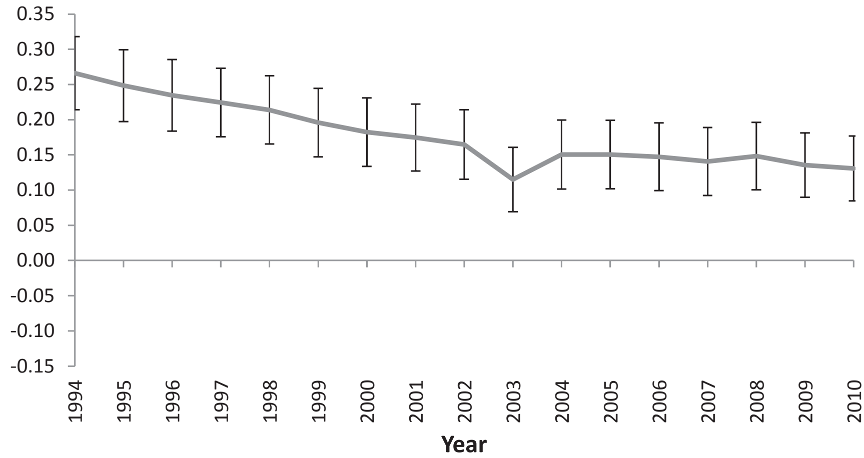
Input-output data are only available at the 2-digit level. Because we use industries at the

Figure 5.10: Coherence of labor market regions' resource bases (NACE-relatedness)



See Figure 5.4.

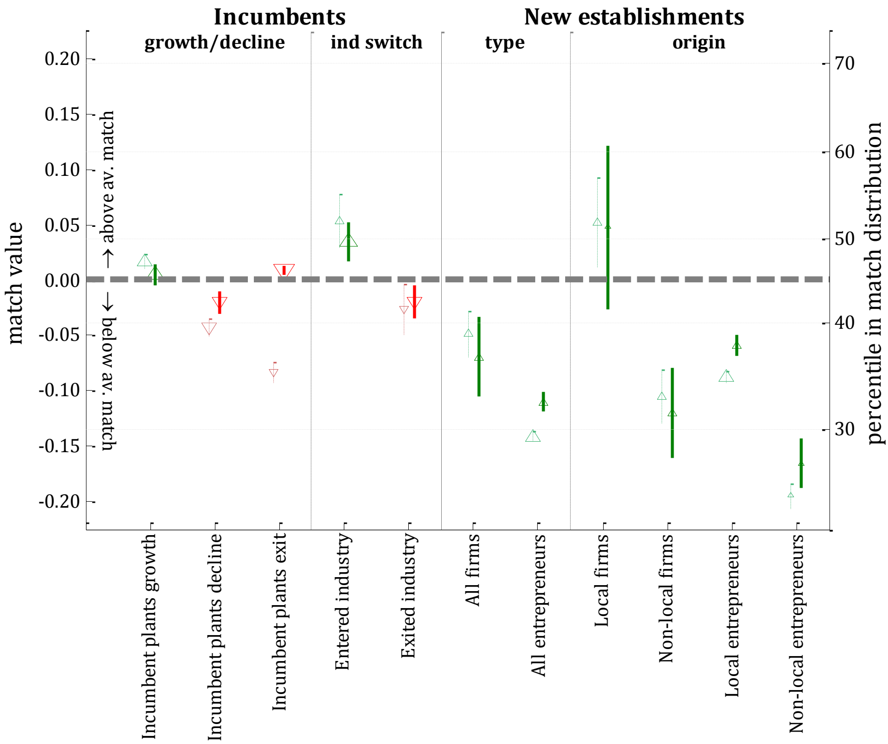
Figure 5.11: Structural change in Sweden's labor market regions (NACE-relatedness)



See Figure 5.5.

4-digit level, we assume that the input-output linkages that exist between two 2-digit sectors are representative of the linkages that exist among the 4-digit industries of which these sectors comprise. We choose the threshold value when two industries are related in such a way that the same number of industry-pairs are input-output related as skill related. Below, we present the outcomes when IOR is used as the relatedness measure:

Figure 5.12: Structural change by agent type (NACE-relatedness)



See Figure 5.9.

Table 5.10: Average resource match of non-local agents to home and host region (input-output relatedness)

Agent type	Resource match to:		p-value
	home region	host region	
Non-local expanding firms	0.096 (0.007)	-0.075 (0.007)	0.000
Non-local entrepreneurs	-0.029 (0.003)	-0.058 (0.003)	0.000

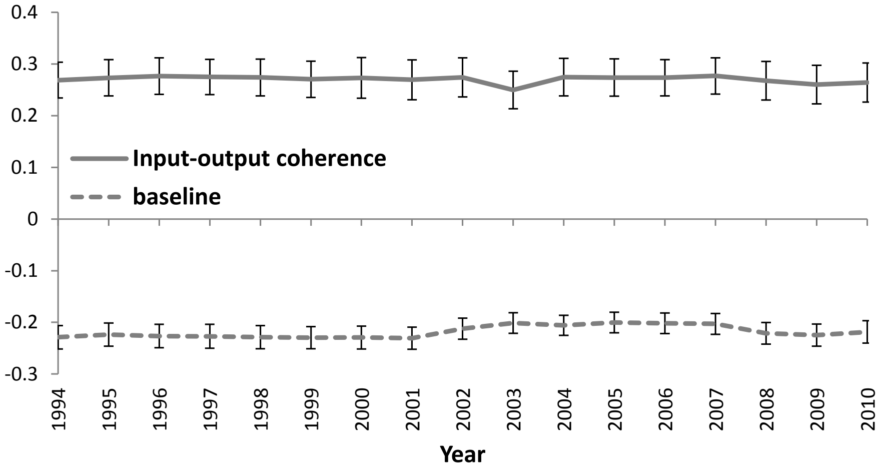
See Table 5.6.

Table 5.11: Establishments' 10-year survival rates (input-output relatedness), *Dep. var.: ≥10 yr survival (0/1)*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Non-local agent	-0.021*** (0.004)	-0.002 (0.012)				
Firm agent			0.073*** (0.009)	0.13*** (0.028)		
Local firm					0.041** (0.016)	0.113* (0.061)
Non-local firm					0.074*** (0.01)	0.108*** (0.032)
Non-local entrepreneur					-0.037*** (0.004)	-0.03** (0.012)
Local X ln(rel. emp.)		0.008*** (0.003)				
Non-local X ln(rel. emp.)		0.005* (0.003)				
Firm X ln(rel. emp.)				0.001 (0.004)		
Entrepreneur X ln(rel. emp.)				0.008*** (0.003)		
Local Firm X ln(rel. emp.)						-0.001 (0.007)
Non-local firm X ln(rel. emp.)						0.003 (0.004)
Local entrepr. X ln(rel. emp.)						0.007*** (0.003)
Non-local entrepr. X ln(rel. emp.)						0.006** (0.003)
Constant	0.157*** (0.005)	0.073** (0.031)	0.153*** (0.005)	0.067** (0.03)	0.156*** (0.005)	0.078** (0.031)
Entry-year FEs included?	yes	yes	yes	yes	yes	yes
Industry FEs included?	yes	yes	yes	yes	yes	yes
Region FEs included?	yes	yes	yes	yes	yes	yes
Number of observations	54055	54055	54055	54055	54055	54055
R-square	0.0254	0.0256	0.0265	0.0268	0.0280	0.0282

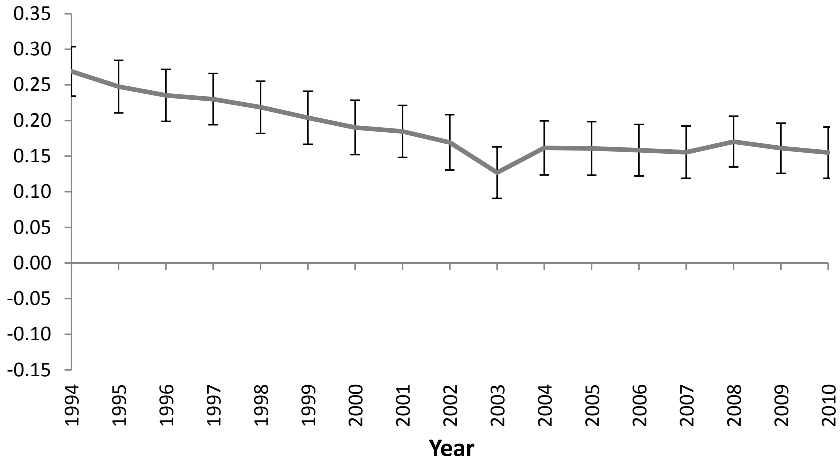
See Table 5.5.

Figure 5.13: Coherence of labor market regions' resource bases (input-output relatedness)



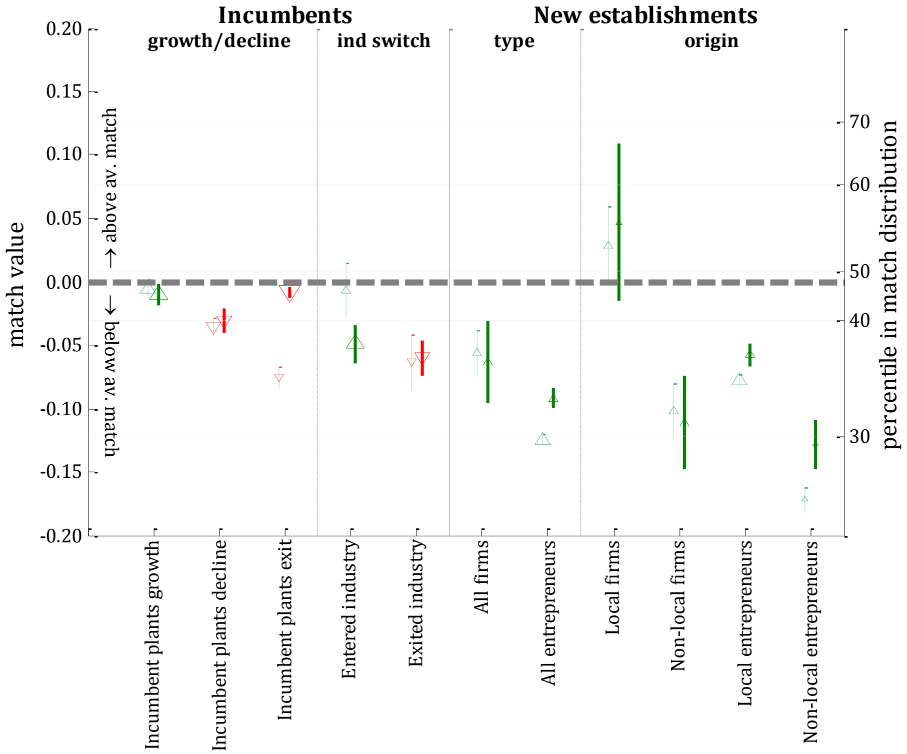
See Figure 5.4.

Figure 5.14: Structural change in Sweden's labor market regions (input-output relatedness)



See Figure 5.5.

Figure 5.15: Structural change by agent type (input-output relatedness)



See Figure 5.9.

6.

The impact of new top managers and top technicians on plant diversification

6.1. Introduction

Having investigated how structural change at the regional level is induced by which agents, the next question is how such change happens at the organizational level. The diversification of firms into new activities and the entry and exit of firms are important sources of resource allocation across economies. A huge literature exists on the implications of firm entries and exits for industry dynamics (Foster et al., 2006; Hansberg and Wright, 2007). At the same time, the recent upsurge of research using national tax registries reveals the broad scope of firm diversification. For instance, in the US, every 5 years 50% of the manufacturing firms alter their product portfolio, and these firms account for 89% of all manufacturing output (Bernard et al., 2010).

To explain diversification, the literature on the resource based view of the firm (following Penrose, 1959) has focused on how excess resources arise in a firm's existing resources and how they can be re-employed into new activities. Excess resources are viewed as emerging endogenously out of a firm's existing activities, for instance due to economies of scope and learning-by-doing. As a result, firms are expected, and have been found, to diversify into related activities by re-deploying these resources.

At the same time, plants acquire new resources through the recruitment of workers. Much less is known about their impact on diversification. This study investigates the impact of new top managers and top technicians. Are plants more likely to diversify after recruiting human capital very different from the plant's main activity? If so, is newly-recruited human capital reflected in future activities of the plant? These questions link diversification at the macro level of the plant to human capital at the micro level of the worker. Foss (2011), in an overview of the existing literature on diversification, referred to this as so far being "*largely an unfilled promise*". A key reason for this are endogeneity concerns. For instance, the hiring of an unrelated top technician might simply reflect the fact that a plant is pursuing a strategy of unrelated diversification. If so, the link between hiring an unrelated top technician and diversifying into unrelated activities would not reflect the effect of an unrelated top technician coming into the plant as such, but rather the plant's strategy that affects both the hiring decision and the diversification move.

To overcome these and other endogeneity concerns and to provide causal evidence of the impact of newly-recruited top managers and top technicians on plant diversification, this study develops the following identification strategy. First, a situation is identified when a top manager or top technician, arguably, is replaced for exogenous reasons, namely when one of a plant's existing top managers or top technicians passes away or emigrates permanently. Because such plants might be plants with specific properties, for instance having an older workforce, propensity score matching is used to create a control group that serves as a counterfactual. This counterfactual represents what the plant outcome would have been had the plants in question not experienced the loss of one's top manager or top technician. The second part of the identification strategy uses a local supply shift instrument to predict the degree of relatedness in human capital between a newly-recruited top manager or top technician and a plant. Adopted from the labor economics literature, it identifies exogenous variation in the availability of human capital in the local supply pool of candidates from which plants recruit.

In the analysis, matched employer-employee data from the administrative records of Statistics Sweden are used, which cover the full population of workers and plants between 1995 and 2010. These are the same data as used in Chapter 5. The occupation of workers is known, as well as the plants they work for and the plants' activities over time. The employment history of workers is used to determine their human capital. This makes it possible to focus on the qualitative part of the human capital of workers and how it matches with the plants they enter, rather than using an aggregated measure at the macro level such as average years of schooling to determine the amount of human capital in a plant. As plants from the whole economy are part of the sample, the findings of the paper cover a different subset of organizations than those of most research on firm diversification, which has primarily focused on larger organizations, particularly those listed on stock exchanges.

The structure of the study is as follows. The second section outlines existing insights on diversification and the impact of managers and technicians. The third section outlines the empirical framework. The fourth section presents the results, and the fifth section concludes and outlines avenues for future research.

6.2. Recruitment, human capital and diversification

According to the resource-based view of the firm, firms diversify to employ idle or underused resources in new activities (Penrose, 1959). Because firms are bundles of idiosyncratic resources (Rumelt, 1982; Wernerfelt, 1984; Barney, 1991), they operate most efficiently when they maximize the resources employed at their disposition. Because learning-by-doing may lead to idle resources, firms can benefit from leveraging those resources into new activities. A single resource may also be able to foster a variety of activities, of which only some are currently pursued by a firm.

A key resource for diversification is the human capital of a firm's workforce. Becker (2002, p. 3) defines human capital as the "*knowledge, information, ideas, skills, and health of individuals*". Individuals acquire human capital through education and work. Unlike physical means of production, such as machinery, which can often be used for one task, human capital is neither specific to one task nor as generic as to cover all tasks possible. Teece (1982, p. 45) refers to this as the 'fungibility of human capital': "*human capital inputs employed by the firm are not always entirely specialized to the particular products and services which the enterprise is currently producing*".

Hence, a firm's human capital can be exploited to undertake activities other than the firm's core activity. Indeed, firms are more likely to diversify into activities in which they can re-employ the human capital of its workforce (Farjoun, 1994; Chang and Singh, 1999; Neffke and Henning, 2013). As this maximizes the value of a firm's human capital, firms can achieve sustainable competitive advantage doing so (Barney, 1991; Peteraf, 1993; Wright et al., 1994).

Indeed, Alchian and Demsetz (1972, p. 793) write that "*Efficient production with heterogeneous resources is a result not of having better resources but in knowing more accurately the relative productive performances of those resources*".

In this respect, most attention has been paid to the emergence of managerial and technical excess resources. As Teece (1982, p. 47) writes: "*A specialized firm's generation of excess resources, both managerial and technical, and their fungible character is critical to the theory of diversification advanced here*". Top managers decide on resource deployment and the firm's strategy (Barney, 1986; Menz, 2012). The ability of managers to lead firms onto new profitable paths is one of the key dynamic capabilities identified by Teece and Pisano (1994). It has been found that managerial actions can make a firm's human capital less imitable and more firm-specific, and thus more competitive (Denrell et al., 2003; Sirmon et al., 2007). As such, manager-specific effects have been found to account for substantial variation in firm performance (Bertrand and Schoar, 2003; Adams et al., 2005) and firm strategies such as leverage decisions (Frank and Goyal, 2007) and tax choices (Bamber et al., 2010; Dyreng et al., 2010).

Regarding the human capital of managers and firm outcomes, most studies have investigated the composition of top management teams following Hambrick and Mason (1984). The level and breadth of a management team's human capital, such as reflected in the composition of educational backgrounds, has been found to affect the speed to respond to competitors' initiatives (Hambrick et al., 1996) and other strategies such as foreign expansion (Hitt and Tyler, 1991; Barkema and Shvyrkov, 2007). Also, individual managers, particularly CEOs, with a technical background have been found to stay closer to the core activities of the firm in forming alliances and when investing in new activities (Tyler and Steensma, 1998).
Rather than focusing on existing managers, and possible excess resources that become available to them over time, this chapter focuses on newly-recruited managers and the human capital they possess and infuse into the organization they enter. Are plants with new managerial human capital more likely to diversify into new activities? If so, do new activities reflect the human capital of the newly-recruited manager? An unrelated manager might, for instance, reduce monitoring costs by pursuing a strategy of aligning the firm's current production resources with his own specialization by re-assigning workers to activities that he is more familiar with.

In this respect, a key aim of the chapter is to separate the impact of a new manager coming into a firm from the impact of other factors, particularly confounding pre-defined strategies of a firm. Whilst much literature exists on management turnover and its effect on firm outcomes, a key question is what is the causal relation driving the outcomes (Lennox et al., 2012; Nandialath et al., 2014; Clougherty and Duso, 2015). A firm might pursue a strategy of diversification into new activities, and might hire an unrelated manager for this purpose. In this case, the association found between hiring an unrelated manager and diversifying into new activities would reflect the firm's strategy rather than the impact of an unrelated manager coming in as such. Hence, one needs to isolate the effect as such of having new managerial human capital come into an organization, which the identification strategy developed in the next section aims to do. The following hypotheses are investigated:

Hypothesis 1: The more the human capital of a new manager differs from the core activity of a plant, the more likely a plant is to diversify

Hypothesis 2: Conditional on diversification, a plant is more likely to diversify into activity j when the human capital of a new manager is related to activity j

As managerial human capital enables plant-internal re-combination of existing and new capabilities, the third hypothesis is as follows:

Hypothesis 3: Conditional on diversification, a plant is more likely to diversify into activity j when both the plant's core activity and the human capital of a new manager is related to activity j

These outcomes are compared to the inflow of human capital by newly-recruited top technicians. More research, particularly due to the availability of patent data to track inventor mobility, has been done on their impact on diversification. They are hands-on involved in the production of output and may thus be the drivers of economies of scope when diversifying into new activities (Teece, 1980; Nayyar and Kazanjian, 1993). The recruitment of high-skilled workers such as scientists and engineers has been found to alter the activities of firms, which tend to diversify into new activities that relate to the background of the new scientists and engineers (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Song et al., 2003; Tzabbar, 2009). A key question again concerns the causality of these results. Similar to the hypotheses regarding new managers, the following hypotheses are investigated:

Hypothesis 4: The more the human capital of a new technician differs from the core activity of a plant, the more likely a plant is to diversify

Hypothesis 5: Conditional on diversification, a plant is more likely to diversify into activity j when the human capital of a new technician is related to activity j

Hypothesis 6: Conditional on diversification, a plant is more likely to diversify into activity j when both the plant's core activity and the human capital of a new technician is related to activity j

6.3. Methodology

6.3.1 Data

Matched employer-employee data from Swedish administrative records that cover the full population between 1995 and 2010 are used. These are the same data as used in the previous chapter. From 2001 onwards, the occupation of workers in plants is known, which is used to distinguish managers from technicians. These are classified according to the Swedish Standard Classification of Occupations, which is based on the International Standard Classification of Occupations from the International Labor Organization.

All plants in the private sector that existed between 2002 and 2008 are part of the sample (2001 is used to construct one of the instrumental variables). Plant-year observations are the unit of analysis. From these plants, those that have at least 5 employees (to exclude freelancers and to accurately identify take-overs later on) and that have a maximum of 250 employees are kept. Plants above this maximum are excluded to exclude the outliers in the tail of the plant size distribution with very large workforces in comparison to the rest of the economy (concerning less than 1% of all plants in the economy).

A newly-recruited top manager or top technician is defined as a worker who first appears in a plant in year t, whose occupation is manager or technician, and who is paid at least the median of the wages of the corresponding occupation in the plant before the recruitment. Hence, the most important managers and technicians in the plants are identified. The impact of them coming into a plant is estimated on the chance of the plant having diversified between t and $t+2$.

Diversification is defined as a change in the first 3 digits of a plant's industry code. This code reflects the main activity of a plant and is measured at the 5-digit level according to the Swedish Standard Industrial Classification 2002, which reflects the EU's NACE Rev 1.1 classification[22]. It only changes after multiple check-ups by the tax office and Statistics Sweden as to whether a plant has truly changed its main activity. Only changes in the first 3 digits of the industry code are taken into account to only register substantial changes in plants' activities.

6.3.2 Human capital match between plant and new top manager or top technician

The variable of interest is the match of the human capital of a newly-recruited top manager or top technician to the plant, which is inferred from the extent to which the industry he or she is recruited from employs similar human capital as the industry of the plant he enters. As in the previous chapter inter-industry human capital similarity is calculated using data on inter-industry labor mobility flows (following Ellison et al. (2010) and Neffke and Henning (2013)). This is based on the idea that people want to minimize the destruction of their human capital when switching jobs and hence tend to switch to industries in which they can re-employ their human capital. As noted later, information on a new recruit's penultimate job is also used,

22 Because the years 1995-2000 are used to calculate human capital similarity between industries, a concordance between the Swedish SNI92 and SNI2002 industry classifications was created and used in the analysis.

as well as a measure of human capital similarity based on the NACE industry classification. Inter-industry human capital similarity, or skill relatedness, is calculated using inter-industry labor flows in Sweden between 1995 and 2000. After selecting the workforce, consisting of the people aged 18 to 65, skill relatedness SR is calculated annually between 1995 and 2000. Formally, let year be indexed by t and summation over omitted categories be indicated by '.', which yields:

$$SR_{ijt} = \frac{F_{ijt}}{(F_{.jt}F_{i.t})/F_{..t}} \qquad \text{(Eq. 6.1)}$$

where F_{ij} is the observed labor flow from industry i to industry j. Industries are defined at the 3-digit level (220 in total). Where a dot replaces the index i or j, the labor flows are summed over this omitted category, such that $F_{i.} = \sum_j F_{ij}$, $F_{.j} = \sum_i F_{ij}$ and $F_{..} = \sum_{i,j} F_{ij}$ The term $(F_{i.}F_{.j})/F_{..} = F_{i.}\frac{F_{.j}}{F_{..}}$ represents the expected flows from i to j, assuming that j receives workers from i proportional to j's share in the total labor flows. SR_{ij} values higher than 1 indicate that industries are skill-related, whereas values between 0 and 1 indicate that industries are unrelated. Because this measure is highly asymmetric, ranging from zero to 1 and from 1 to infinity, we use map SR_{ijt} onto the interval [-1, 1):

$$\widetilde{SR}_{ijt} = \frac{SR_{ijt}-1}{SR_{ijt}+1} \qquad \text{(Eq. 6.2)}$$

Hence, industry i is skill related to industry j if $\widetilde{SR}_{ijt} > 0$. Then, for every industry-industry pair, we average $\widetilde{SR}_{ijt}$ over all flows between 1995 and 2000:

$$M\widetilde{SR}_{ij} = \frac{1}{5}\sum_{t=1995}^{2000} \widetilde{SR}_{ijt} \qquad \text{(Eq. 6.3)}$$

Finally, we symmetrize the measure so that $S\widetilde{SR}_{ij} = S\widetilde{SR}_{ji}$:

$$S\widetilde{SR}_{ij} = \frac{M\widetilde{SR}_{ij} + M\widetilde{SR}_{ji}}{2} \qquad \text{(Eq. 6.4)}$$

which is the measure of inter-industry human capital similarity that is used in the analyses.

6.3.3 Identification strategy

Recruitment is endogenous because plants choose whether and whom to recruit. Hence, to obtain an estimate of the causal effect of new recruits on plant outcomes, one has to tease out unobservable time-variant and invariant effects. Particularly those related to a plant's possible diversification strategy are a concern. To deal with this, the following identification strategy is developed. First, a situation is identified in which a top manager or top technician is replaced due to arguably exogenous reasons, namely when one's top manager or top technician passes away or emigrates permanently. Second, to instrument the degree of human capital similarity of a new top manager or top technician to the plant, exogenous variation is identified in the supply pool of candidates from which plants recruit. In doing so, exogenous shifts over the past 15 years in Sweden in the amount of graduates with certain skills that enter the local labor markets are used.

Losing one's top manager or top technician as a result of death or permanent emigration

The situation in which a plant has to recruit a new top manager or top technician regardless of its pre-existing strategy is identified by when one of its top managers or top technicians passes away or emigrates permanently (i.e. does not return to Sweden). Such loss to a plant is identified by the fact that a worker disappears from the Swedish administrative records in year t and does not re-appear in subsequent years. For instance, a worker that last appears in the records in 2001 and does not re-appear until at least 2011 (the last year of data available), is regarded as having passed away or having emigrated permanently. Excluded are people that were born outside of Sweden as they might move in and out of the administrative records more frequently for other reasons.

Plants that experience such a loss are unlikely to be similar to any other plant randomly picked from the Swedish population of plants. For instance, as the chance of passing away increases with age, plants with older top managers more likely experience a top manager's death. Such plant properties might affect the chance of diversification as well (e.g. plants with an older workforce might be less likely to diversify due to a lock-in effect), which would confound the results.

Therefore, a counterfactual to those plants is created by creating a control group, the aim of which is to infer how the plant outcome would have been had plants not experienced the loss of one's top manager or top technician. This is done by propensity score matching. Losing a top manager or top technician due to death or permanent emigration is regressed on variables related to the size and age of the plant, industry, being part of a multi-plant firm, employment growth of the past 3 years (hence only included are plants that have existed for at least 3 years), the age distribution of the workforce of the plant (how many workers it employs between 18 and 30, 31 and 40, and so on) the gender and mean age and educational level of its top manager(s)/top technician(s), as well as the interaction between educational level of the latter and size of the plant. From the propensity score that follows, a control group of 'statistical twins' is created for every plant that lost a top manager or top technician. This is done using k-nearest-neighbor matching by matching every of those plants to 10 plants in the economy that have propensity scores that are closest to the propensity score of the plant, whilst matching exactly on the year in which the plants and control plants are observed[23].

Using this sample of plants, a Heckman correction (Heckman, 1979) to the recruitment

23 Because plant-year observations are the unit of analysis, it is made sure that a treated plant in one year cannot be assigned to the control group in previous or subsequent years as this may confound the results because the effect of death/emigration of one's top manager/top technician on plant outcomes may stretch across years.

of a top manager or top technician is applied. First, a probit regression is ran to predict the hiring of a new top manager or top technician following the loss of (one of) its pre-existing one(s). The Inverse Mills Ratio that results is included in subsequent regressions, capturing the selection effect of the decision of a plant to hire a new top manager or top technician. The decision as such to hire a new top manager or top technician is then arguably identified in a situation that is exogenous to particular pre-defined plant strategies, particularly strategies related to diversification.

Local supply shifts in the availability of human capital

Plants choose not only whether to hire, which the Heckman correction aims to address, but also what kind of employee is recruited. Hence, it is also necessary to identify exogenous variation in the degree of human capital similarity of new recruits to a plant. This is done by exploiting exogenous variation in the availability of human capital in the supply pool of candidates from which plants recruit – with the idea that once the local supply of human capital related to the plant increases, there is downward pressure on the wages associated with it, which makes such human capital more attractive for plants to hire. An instrument to predict local supply shifts in labor market areas is created that builds on the "shift-and-share" approach that was introduced by Bartik (1991) and that has subsequently been used in different adaptations by others in labor economics (Card, 2007; Moretti, 2010; Faggio and Overman, 2014).

The instrument uses shifts over the past 15 years in the local availability of graduates with certain degrees. For instance, had there been substantial growth in graduates with a degree in computer science in the south-Swedish city of Lund over the past decade (i.e. many more people from Lund would have graduated with such a degree each year), such increasing supply would have put downward pressure on the wages of people with such human capital. This would make such people more attractive for plants in Lund to hire. However, such a local supply shift is endogenous to local plants if, for instance, it has been driven by university-industry collaboration in the region. Hence, following the core idea of Bartik (1991), national growth rates of graduates with certain degrees in Sweden are exploited.

First, let $\mathrm{G}_{\mathrm{cmb}}$ be the number of graduates G with degree type c in municipality m in base period b (where municipality is the place where students lived at the time of graduation). The base period goes from 1990 until 1995 (in 1995 a major reform of education was undertaken in Sweden). Here, $\mathrm{G}_{\mathrm{cmb}}$ measures the initial distribution of graduates with certain degrees across municipalities. Next, the predicted number of graduates with a certain degree in a municipality in future year t is calculated based on the national growth of the corresponding graduates. In national growth, the municipality itself is excluded:

$$\mathrm{PG}_{\mathrm{cmt}} = \frac{(\mathrm{G}_{\mathrm{cmb}}/\mathrm{G}_{\mathrm{cb}})}{(1-(\mathrm{G}_{\mathrm{cmb}}/\mathrm{G}_{\mathrm{cb}}))} \times (\mathrm{G}_{\mathrm{ct}} - \mathrm{G}_{\mathrm{cmt}}) \qquad \text{(Eq. 6.5)}$$

which reflects the number of graduates with degree c in municipality m in year t had the supply of graduates with degree c in municipality m grown according to the national trend. Because regional growth rates for the municipality in question are excluded from it, it should be exogenous to local plants.

The next step calculates which educational degrees are overrepresented in which occupation-industry combinations. For instance, technicians in the aerospace industry might be more likely to possess an aerospace engineering degree than other occupation-industries. Let E_{ciot} be the number of workers E with degree c employed in industry i with occupation o in year t, then our specialization measure is constructed as follows:

$$\mathrm{S}_{iot}^{c} = \frac{(\mathrm{E}_{ciot}/\mathrm{E}_{iot})}{(\mathrm{E}_{ct}/\mathrm{E}_{t})} \qquad \text{(Eq. 6.6)}$$

which goes from 0 to 1 (a degree is under-represented in a certain occupation-industry) and from >1 to infinity (over-represented). This measure is created using the full workforce of Sweden in 2001. Linking this measure to the supply shift measure of Eq. (6.5), it is now possible to count how many graduates that would be particularly valuable for occupation o in industry i are expected to graduate in a given city:

$$\mathrm{G}_{iomt} = \sum_{c} \mathrm{PG}_{cmt} * \mathrm{I}(\mathrm{S}_{iot}^{c} > 1) \qquad \text{(Eq. 6.7)}$$

where $\mathrm{I}(\mathrm{S}_{iot}^{c} > 1)$ is an indicator function that is either 0 or 1. This measure predicts the number of graduates in year t in municipality m that are suitable for industry i with occupation o. This measure is transformed to the municipality-industry level using the inter-industry skill-relatedness measure created earlier:

$$\mathrm{G}_{iomt}^{rel} = \sum_{c} \mathrm{G}_{jomt} * \mathrm{I}(\mathrm{SR}_{ij} > 1) \qquad \text{(Eq. 6.8)}$$

The intuition behind this measure is that if, for instance, there is an increase of graduates in a region suitable for being a technician in the automobile industry (industry j in this example), it would put downward pressure on the wages of the technicians in the automobile industry in the region and hence make them more attractive to hire. In turn, if industry j is skill-related to industry i (e.g. motorcycle producers), this would increase the chance of industry i hiring a related rather than an unrelated technician.

To calculate the shift of local supply, the measure above is divided by the total number of people in a municipality with degrees suitable for industry j which are related to industry i:

$$\mathrm{SHIFT}_{iomt}^{rel} = \mathrm{G}_{iomt}^{rel} \Big/ \mathrm{Gpop}_{iomt}^{rel} \qquad \text{(Eq. 6.9)}$$

Finally, this measure is aggregated from the municipal level to the labor market level as the latter is more appropriate when recruitment of plants is concerned. 110 labor market regions are distinguished by Statistics Sweden based on commuting patterns of workers between place of living and place of work. In sum, at deposition now is a local supply shift instrument that identifies exogenous variation in the local supply pool of human capital from which plants recruit.

Correcting for measurement error

In comparing the endogenous regressions to the regressions using the identification strategy above, it is informative to get an estimate of how much bias the coefficients contain due to measurement error (biasing the coefficients towards zero, thus reflecting no effect). The instrumental regressions pick up measurement error in conjunction with omitted variable bias originating from for instance a firm's strategy. By separating these effects, a more accurate estimate of omitted variable bias is possible.

The first source of measurement error originates from the inter-industry human capital similarity measure. Therefore, another relatedness measure is created based on the NACE industry classification and its hierarchical structure, part of which captures inter-industry human capital similarity. Every industry-industry pair is assigned a value of 0 (different 1-digit industries) to 3 (same 3-digit industries). This measure is correlated with the skill relatedness SSR value ($r = 0.23$). As the construction of the NACE classification is based on a wholly different logic and methodology, instrumenting the SSR measure with NACE-relatedness should rid the coefficients of the measurement error that originates from the measurement of inter-industry human capital similarity.

Another source of measurement error originates from the fact that the human capital match of a new employee is measured by the skill relatedness between the industry of the plant he or she enters and the industry he or she is recruited from. However, one's human capital is the experience one has accumulated in all of the industries he or she has previously worked in, as well as the education that he or she has followed. Therefore, the SSR measure is also instrumented with the NACE-relatedness of the plant's industry to the penultimate industry a new recruit worked in (the industry the recruit worked in before he or she started working in the industry where he or she was recruited from).

6.4. Results

Of all plant-year observations that have at least 1 manager (264333 in total), 726 experience the death or permanent emigration of a top manager, and of all plant-year observations that have at least 1 technician (106390 in total), 550 experience such an event. Hence, losing one's top manager or top technician due to these reasons is a relatively rare event.

The propensity score matching procedure results in a control group of 6929 plants that have at least 1 top manager, and a control group of 5007 plants that have at least 1 technician[24]. Comparative statistics on the matching variables of the control group after matching, and the control group if it were consisting of the full population of plants, are presented in Table 6.1 (top managers) and Table 6.2 (top technicians). As can be seen, plants that lost a top manager or top technician tend to have a larger workforce and older and better-educated top managers and top technicians than the average plant in the population. The matching procedure substantially improves the comparability with the control group, as can be seen from the large reduction of % bias in almost all of the variables in both tables.

Table 6.3 shows that about 15% of the plants have exited after 2 years due to failure or being taken over and about 5% of the plants have diversified (this diversification percentage is much higher when changes in plants' industry code at the 4-digit or 5-digit would be taken into account). Table 6.4 (top managers) and Table 6.5 (top technicians) show the impact of the death/permanent emigration of a top manager/top technician on exit due to failure, diversification and take-over of the plants (survival is the reference category). The relative risk ratios show that plants are about twice as likely to exit due to failure or take-over following the loss of a top manager. The exit due to failure effect is similar for the loss of a top technician, only the take-over effect is a bit smaller (1.5). There is no significant impact on the chance of diversifying in either of the groups. The coefficient of the death/permanent emigration variable in both tables in Model 1 does not differ significantly from its corresponding coefficient in Model 2 that includes the matching variables as regressors, which implies that there are no longer confounding effects of these variables on the plant outcomes.

Table 6.6 (top managers) and Table 6.7 (top technicians) show the effect of recruiting a new top manager/top technician on the chance of diversifying into a new industry. This is conditional on survival, hence only survivors are included (the balance on the matching variables does not change significantly for this group). Linear probability models are used to facilitate interpretation with the corresponding 2SLS regressions, which are more developed than instrumental probit or logit regressions in terms of assessing instrument strength and reliability (Angrist and Pischke, 2009). The results show that the hiring of a top manager has no impact on diversification, neither in the OLS nor in the 2SLS regressions that use the death or permanent emigration of an existing top manager as instrument. The hiring of a top technician raises the probability of diversification only in the OLS regressions. The instrument of death/permanent emigration, however, does not work well for top technicians, as can be seen from the low Cragg-Donald F statistics in Table 6.7. Hence, top technicians, once lost, are not necessarily replaced by new top technicians by plants, contrary to top managers.

24 The sum of these numbers is not equal to the size of the group multiplied by 10 because the propensity score matching procedure sometimes assigns the same plant as a control (counterfactual) to multiple plants that experienced a loss.

Table 6.1: Propensity score matching variable results: loss of one's top manager

Variable	Mean: group	Mean: Control group full population	% bias	Mean: Control group after matching	% bias
Multi-plant firm	0.249	0.247	0.6	0.25	-0.8
Manufacturing industry	0.205	0.188	4.4	0.198	2.2
Age plant	11.111	10.746	10	11.132	-0.6
Employment plant (log)	2.899	2.674	24.1	2.886	0.2
Employment growth plant - last 3 years	1.242	1.347	-8.4	1.256	-1.4
Mean age top manager(s)	52.688	47.545	53.7	52.734	-0.1
Gender top manager(s)	1.107	1.15	-13.5	1.113	-2.2
N of top manager(s) with primary educ. < 9 years	0.104	0.053	18.3	0.1	1.4
N of top manager(s) with primary educ. => 9 years	0.136	0.129	1.8	0.132	0.4
N of top manager(s) with upper secondary education	0.57	0.567	0.4	0.557	0.3
N of top manager(s) with post-secondary educ. < 2 years	0.129	0.137	-2.3	0.122	1.4
N of top manager(s) with post-secondary educ. => 2 years	0.44	0.259	25.7	0.393	2.1
N of top manager(s) with post-graduate education	0.021	0.008	10.3	0.017	1.3
N of top manager(s) with other education (9)	0.012	0.004	8.7	0.011	1.4
Mean age workforce	41.749	40.133	25	41.698	0.7
N of workers aged 18 - 30	7.73	5.966	14.6	7.68	-0.6
N of workers aged 31 - 40	9.233	6.2	25.2	8.954	0.6
N of workers aged 41 - 50	7.204	5.065	22.6	7.065	0.2
N of workers aged 51 - 60	6.11	4.09	24.2	6.028	-0.2
N of workers aged 61 - 64	1.711	1.044	26	1.671	0.1
N of workers aged 64	0.31	0.181	19.8	0.299	0.2
N of workers aged 64 and higher	0.504	0.316	19.9	0.486	1.5
Emp_plant X N of top manager(s) with primary educ. < 9 years	0.282	0.132	18.4	0.267	1.8
Emp_plant X N of top manager(s) with primary educ. => 9 years	0.368	0.335	3.3	0.355	0.3
Emp_plant X N of top manager(s) with upper secondary education	1.754	1.528	9.7	1.682	0.5
Emp_plant X N of top manager(s) with post-secondary educ. < 2 years	0.443	0.403	3.3	0.41	1.7
Emp_plant X N of top manager(s) with post-secondary educ. => 2 years	1.597	0.811	26.2	1.372	2.3
Emp_plant X N of top manager(s) with post-graduate education	0.071	0.027	10	0.061	0.8
Emp_plant X N of top manager(s) with other education (9)	0.04	0.013	9.1	0.033	1.8

Table 6.2: Propensity score matching variable results: loss of one's top technician

Variable	*Mean: group*	*Mean: Control group full population*	*% bias*	*Mean: Control group: after matching*	*% bias*
Multi-plant firm	0.391	0.304	18.4	0.391	0
Manufacturing industry	0.256	0.242	3.3	0.254	0.4
Age plant	10.713	10.558	3.9	10.794	-2.1
Employment plant (log)	3.406	2.93	48.2	3.382	2.3
Employment growth plant - last 3 years	1.458	1.425	1.8	1.438	1.1
Mean age top technician(s)	44.933	42.498	24.8	45.361	-4.5
Gender top technician(s)	1.119	1.12	-0.5	1.121	-1.1
N of top technician(s) with primary educ. < 9 years	0.051	0.03	10.2	0.062	-4.1
N of top technician(s) with primary educ. => 9 years	0.178	0.112	15.3	0.181	-0.5
N of top technician(s) with upper secondary education	2.193	1.08	49.9	2.055	5.1
N of top technician(s) with post-secondary educ. < 2 years	1.302	0.55	51.3	1.212	5.1
N of top technician(s) with post-secondary educ. => 2 years	2.967	1.07	64.3	2.658	8.4
N of top technician(s) with post-graduate education	0.238	0.058	25.3	0.128	14.3
N of top technician(s) with other education (9)	0.027	0.006	13.5	0.013	8.6
Mean age workforce	41.379	40.984	6.9	41.52	-2.5
N of workers aged 18 - 30	10.155	6.91	25.8	10.03	0.9
N of workers aged 31 - 40	15.435	8.907	44.8	14.697	4.4
N of workers aged 41 - 50	12.033	7.147	39.2	11.645	2.7
N of workers aged 51 - 60	9.551	5.649	33.6	9.236	2.4
N of workers aged 61 - 64	2.567	1.453	31.2	2.516	1.3
N of workers aged 64	0.425	0.249	20.7	0.433	-0.7
N of workers aged 64 and higher	0.545	0.393	14.5	0.538	0.6
Emp_plant X N of top technician(s) with primary educ. < 9 years	0.207	0.103	12.1	0.249	-3.8
Emp_plant X N of top technician(s) with primary educ. => 9 years	0.721	0.377	19.4	0.726	-0.2
Emp_plant X N of top technician(s) with upper secondary education	8.642	3.567	51.5	7.934	5.9
Emp_plant X N of top technician(s) with post-secondary educ. < 2 years	5.103	1.824	54.1	4.65	6.1
Emp_plant X N of top technician(s) with post-secondary educ. => 2 years	11.382	3.531	64	9.953	9.3
Emp_plant X N of top technician(s) with post-graduate education	0.95	0.192	27.5	0.479	15.7
Emp_plant X N of top technician(s) with other education (9)	0.105	0.02	14.2	0.045	9.3

Table 6.3: Exit, diversification and survival statistics of plants

	Managers: plants + control group		*Technicians: plants + control groups*	
Variable	*Abs.*	*Rel. (%)*	*Abs.*	*Rel. (%)*
Exit due to failure	312	4 %	234	4%
Survival	6339	83 %	4639	83%
Diversification	273	3%	219	4%
Exit due to take-over	731	10%	465	9%
Total	7655	100%	5557	100%

Table 6.4: Impact of death/permanent emigration of top manager on chance to exit, diversify or being taken-over (reference category: survival) – multinomial logistic regression, presented are relative risk ratios

	(1)			*(2)*		
	Exit due to failure	*Diversification*	*Exit due to take-over*	*Exit due to failure*	*Diversification*	*Exit due to take-over*
Death / perm. emigration top manager	2.253*** (0.352)	1.133 (0.239)	1.915*** (0.227)	2.311*** (0.368)	1.115 (0.237)	1.979*** (0.245)
Constant	0.042*** (0.006)	0.034*** (0.006)	0.002*** (0.001)	0.461 (0.352)	0.021*** (0.020)	0.081*** (0.072)
Year FEs included?	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	no	yes	yes	yes
Observations	7655	7655	7655	7655	7655	7655

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.5: Impact of death/permanent emigration of top technician on chance to exit, diversify or being taken-over (reference category: survival) – multinomial logistic regression, presented are relative risk ratios

	(1)			*(2)*		
	Exit due to failure	*Diversification*	*Exit due to take-over*	*Exit due to failure*	*Diversification*	*Exit due to take-over*
Death / perm. emigration top technician	2.031*** (0.368)	0.987 (0.237)	1.509*** (0.230)	2.042*** (0.377)	0.926 (0.227)	1.515*** (0.237)
Constant	0.041*** (0.006)	0.040*** (0.007)	0.006*** (0.002)	0.058*** (0.052)	0.285 (0.284)	0.043*** (0.033)
Year FEs included?	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	no	yes	yes	yes
Observations	5557	5557	5557	5557	5557	5557

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.6: Impact of recruiting a top manager on chance of plant to diversify – linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	*IV 2SLS*	*OLS*	*IV 2SLS*	*OLS*	*IV 2SLS*	*OLS*	*IV 2SLS*
Recruitment top manager	-0.000 (0.008)	0.014 (0.106)	0.000 (0.008)	0.001 (0.110)	-0.000 (0.008)	-0.004 (0.116)	0.003 (0.008)	-0.013 (0.104)
Constant	0.041*** (0.009)	0.035** (0.014)	0.026 (0.036)	0.029 (0.046)	-0.002 (0.039)	-0.002 (0.042)	0.009 (0.037)	-0.003 (0.044)
R-square	0.001	0.000	0.014	0.014	0.034	0.034	0.034	0.033
Year FEs included?	yes	yes	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	yes	yes	yes	yes	yes	yes
Region FEs included?	no	no	no	no	yes	yes	no	no
Industry FEs included?	no	no	no	no	no	no	yes	yes
Observations	5917	5917	5917	5917	5917	5917	5917	5917
First stage Cragg-Donald F-statistic		23.06		22.77		19.98		24.33

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.7: Impact of recruiting a top technician on chance of plant to diversify – linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	*IV 2SLS*	*OLS*	*IV 2SLS*	*OLS*	*IV 2SLS*	*OLS*	*IV 2SLS*
Recruitment top technician	0.012* (0.006)	-0.132 (0.502)	0.013* (0.007)	-61.252 (21326.398)	0.015** (0.007)	-1.389 (14.058)	0.011 (0.007)	8.168 (339.265)
Constant	0.033*** (0.013)	0.087 (0.192)	0.119** (0.048)	9.638 (3310.734)	0.083 (0.052)	0.631 (5.876)	0.108* (0.059)	2.162 (86.294)
R-square	0.005	-0.112	0.019	-16531.837	0.059	-8.405	0.033	-287.204
Year FEs included?	yes	yes	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	yes	yes	yes	yes	yes	yes
Region FEs included?	no	no	no	no	yes	yes	no	no
Industry FEs included?	no	no	no	no	no	no	yes	yes
Observations	4389	4389	4389	4389	4389	4389	4389	4389
First stage Cragg-Donald F-statistic:		0.746		0.000		0.011		0.001

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.8 (top managers) and Table 6.9 (top technicians) show the impact of the human capital match of a newly-recruited top manager or top technician on diversification. Included are all plants that have hired a new top manager or top technician. Following Wooldridge (1995), the Inverse Mills Ratio from the Heckman correction is included in these regressions (it is not included in the technician regressions as the power of the instrument is too low in their case). As the supply shift instrument relies on region and industry variation, region and industry fixed effects are now excluded. In all models, as expected, the higher the human capital similarity of a new recruit to a plant, the less likely a plant is to diversify into new activities (the base chance is 5%). Hence, support is found for hypotheses 1 and 3.

In these models, the 2SLS coefficients instrumented by the supply shift instrument are higher and less accurate than the OLS coefficients. As noted earlier, part of this may be due to the measurement error involved in measuring the degree of human capital similarity between the plant and the new top manager or top technician. This is confirmed in the 2SLS models that instrument human capital similarity with NACE-relatedness of the penultimate job of the new recruit, which should only take out the measurement error that would reduce the coefficient towards zero. The coefficients strongly increases in these models in comparison to the OLS ones and are now near the corresponding 2SLS ones.

Table 6.10 (top managers) and Table 6.11 (top technicians) investigate the direction of diversification, whether plants are more likely to diversify into industries that are related to their existing activities as well as the human capital of the new top manager or top technician. Because no instruments are used here, all diversifying plants from the full population who have recruited a new top manager or top technician are selected and assigned a vector of all industries they could possibly diversify into (220 in total). A score of 1 is assigned to the industry they have actually they diversified into and a score of 0 to the others. This is then regressed on the human capital match of every of these industries with the plant and the new top manager or top technician.

The results are that plants are more likely to diversify into an industry that is related to the human capital of the new top manager or top technician. The more the latter are related to a target industry, the higher the chance of diversifying into it. Hence, support is found for hypotheses 2 and 4 that plants are more likely to diversify into activities that match the human capital of the new recruit. The interaction term shows that this is especially so when the target industry is related to both the plant's main activity and the human capital of the new top manager or top technician. This supports hypotheses 3 and 6.

Another way of investigating this is by analyzing the chance of diversifying into a related industry rather than an unrelated industry, of which the results are shown in Table 6.12 (top managers) and Table 6.13 (top technicians). Conditional on diversifying, the more the human capital of a new top manager or top technician is related to the plant, the more likely a plant is to diversify into a related industry. Hence, the hiring of an unrelated top manager or top technician increases the chance of diversifying into activities that are unrelated to the plant's main activity, but, as shown in Tables 6.10 and 6.11, such activities are yet often related to the human capital of the new top manager or top technician.

Table 6.8: Impact on diversification chance of degree of relatedness of new top manager to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift
Human capital similarity (SSR) of new top manager(s) to plant	-0.054*** (0.016)	-0.040*** (0.015)	-0.107*** (0.033)	-0.244** (0.120)	-0.051*** (0.017)	-0.034** (0.016)	-0.121*** (0.037)	-0.252* (0.150)
Inverse Mills Ratio	0.097 (0.068)	0.093 (0.068)	0.116 (0.078)	0.151* (0.086)	0.109 (0.071)	0.104 (0.070)	0.134* (0.081)	0.167* (0.092)
Constant	-0.132 (0.120)	-0.090 (0.115)	-0.110 (0.129)	-0.071 (0.131)	-0.383** (0.152)	-0.345** (0.144)	-0.373** (0.161)	-0.306* (0.167)
R-square	0.030	0.028	0.009	-0.214	0.076	0.074	0.052	-0.169
Year FEs included?	yes	yes	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	no	no	yes	yes	yes	yes
Observations	759	759	655	759	759	759	655	759
First stage Cragg-Donald F-statistic		2148	166.8	12.23		1911	114.4	7.586

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.9: Impact on diversification chance of degree of relatedness of new top technician to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS: SR instrumented with NACE previous job	IV 2SLS: SR instrumented with NACE of last job before previous job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: instrumented with NACE previous job	IV 2SLS: instrumented with NACE of last job before previous job	IV 2SLS: graduate supply shift
Human capital similarity (SSR) of new top technician(s) to plant	-0.037***	-0.052***	-0.110***	-0.183***	-0.033***	-0.042***	-0.107***	-0.214**
	(0.012)	(0.014)	(0.030)	(0.062)	(0.012)	(0.014)	(0.036)	(0.099)
Constant	0.037*	0.085***	0.106***	0.145***	0.119	0.175**	0.265***	0.300***
	(0.022)	(0.016)	(0.023)	(0.033)	(0.080)	(0.082)	(0.100)	(0.116)
R-square	0.016	0.015	-0.002	-0.070	0.035	0.035	0.021	-0.087
Year FEs included?	yes	yes	yes	yes	yes	yes	yes	yes
Matching variables included?	no	no	no	no	yes	yes	yes	yes
Observations	1722	1722	1552	1722	1722	1722	1552	1722
First stage Cragg-Donald F-statistic		3465	255.8	68.55		3018	177.8	29.60

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.10: Impact of human capital similarity of new top manager on chance of diversifying into target industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of plant to target industry	0.023*** (0.001)
Human capital similarity (SSR) of new top manager to target industry	0.024*** (0.002)
Interaction: Human capital similarity (SSR) plant X Human capital similarity (SSR) new top manager	0.037*** (0.003)
Constant	0.013*** (0.001)
Observations	84260
R-square	0.03

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.11: Impact of human capital similarity of new top technician on chance of diversifying into a certain industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of plant to target industry	0.024*** (0.001)
Human capital similarity (SSR) of new top technician to target industry	0.026*** (0.001)
Interaction: Human capital similarity (SSR) plant X Human capital similarity (SSR) new top technician	0.041*** (0.002)
Constant	0.014*** (0.001)
Observations	164120
R-square	0.04

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.12: Impact of human capital similarity of new top manager with plant on chance of diversifying into a related industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of new top manager to plant	0.136*** (0.041)
Constant	0.775*** (0.028)
Observations	383
R-square	0.03

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

Table 6.13: Impact of human capital similarity of new top technician with plant on chance of diversifying into a related industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of new top technician to plant	0.198*** (0.034)
Constant	0.766*** (0.021)
Observations	746
R-square	0.06

*Significant at 90%; **Significant at 95%; *** Significant at 99%; Robust standard errors in parentheses

6.5. Conclusion

Using matched employer-employee data from Statistics Sweden, causal evidence is found that the inflow into plants of unrelated top managers and top technicians – those that possess human capital very different from a plant's core activity – increase the chance of plants to diversify into new activities. These new activities tend to be related to the plant's main activity as well as the human capital of the new top manager or top technician. These results are obtained using an identification strategy that uses the death or permanent emigration of an existing top manager or top technician in a plant on the one hand and a supply shift instrument of skill availability in the region to predict what kind of human capital is hired on the other hand. This is to ensure the causality of these results, by excluding omitted variables from confounding the results, particularly those related to firms pursuing a strategy of unrelated diversification and hiring unrelated employees for that purpose. Although managers are often regarded as the most important drivers of diversification, this study finds that their impact is similar to the impact of new top technicians. These results provide micro level evidence into the effect of recruitment and human capital on diversification of organizations, which has been identified as one of key areas for future research on diversification (Foss, 2011).

There are a number of avenues for future research. First, the plants covered in this study range from very small to very large plants. They differ from the type of plants covered in most diversification research, which has focused on large organizations, often those listed on the stock exchange. It may be that in such large firms, the top management team is more important than the top technicians, or that the impact of one is dependent on the degree of human capital similarity with the other. This would require one to investigate the degree of relatedness between both teams, which is especially interesting given that most research has focused on either the diversity of human capital within top management teams (following Hambrick et al., 1996) or inventor teams (Laursen et al., 2015) but not on both of them in conjunction.

Secondly, a key question concerns the functional form of the relationship between the relatedness of a new top manager or top technician to a plant and possible plant outcomes. It might be that there should be neither too much nor too little relatedness for diversification to occur. The reasoning is similar to what has been investigated in Chapter 2 regarding related variety, namely that in the former case there is little to learn from each other, whereas in the latter there may not be enough absorptive capacity to effectively recombine capabilities and learn from each other (Nooteboom et al., 2007). The relationship would then be concave in the form of an inverted-U shape rather than be linear. It might be that if new top managers or top technicians are too unrelated, plants are more likely exit due to incompatibilities. At the same time, it might be that diversification is most successful at some optimal level of relatedness.

Thirdly, there is much to learn from changes in the product portfolios of plants. The data used in this chapter only made it possible to investigate change in a plant's industry code. While this provides information on the shift of a plant's main activity, and its direction, it misses out on what is exactly going on underneath. Plants might drop certain products, might add other ones, and might churn by doing both at the same time, all of which occur quite frequently economy-wide (Bernard et al., 2010). It might be that the recruitment of unrelated managers leads more often to churning, whereas the recruitment of unrelated technicians leads more often to adding products. It is worthwhile for future research to investigate these questions.

7.
Conclusion and future research

7.1 Main findings and contributions

The aim of this PhD thesis is to explain economic development based on economic behavior at the micro level, by focusing on how relatedness and the diffusion of capabilities across firms and regions mechanisms affect development and structural change. Of key interest are the compositions of activities within regions and plants, to what extent these compositions consist of related activities, how they change over time, how they affect the growth and development of new activities, and which knowledge transfer mechanisms are important in this. In investigating this, this PhD thesis strongly draws upon and contributes to the evolutionary approach in economic geography that has emerged over the past two decades, which aims to explain uneven economic development from the spatial distribution of routines over time across organizations. Given the much-publicized struggle of specialized cities such as Detroit to renew themselves and grow again, there is growing interest in this topic.

The first question is how a composition of related activities in regions, or related variety, affects growth. Frenken et al. (2007) explicitly distinguished unrelated variety from related variety in the agglomeration economies literature, finding that the latter is necessary for regional growth. Other studies have found similar results (Boschma and Iammarino, 2009; Bishop and Gripaios, 2011; Boschma et al., 2012). The contribution of Chapter 2 to this debate is to introduce the technological intensity of industries as a moderating factor. Using Finnish data between 1993 and 2006 and System-GMM estimators to deal with endogeneity concerns, it confirms prior findings that related variety is important for regional employment growth, but adds to this insight that only related variety among local high-tech industries matters. This highlights the importance of taking into account sector specificities regarding the effect of related variety on regional growth.

The second question is what determines the creation of inter-organizational knowledge transfer ties. A number of theoretical accounts on the spatial evolution of networks and their effect on regional development have appeared in recent years. Particularly, the proximity literature (following Boschma and Frenken, 2009) has highlighted the importance of different forms of proximity, such as relatedness or cognitive proximity, on tie formation. The contribution of Chapter 3 is to investigate the impact of different forms of proximity on tie formation together with factors at the node and structural network level, which only a few studies have done so far (Balland, 2012; Balland et al., 2013). Using exponential random graph models on the Dutch aviation industry network as observed in 2008, it finds that tie formation is driven by geographical and institutional proximity as well as triadic closure. Including only proximity variables yields models that do not predict the observed network well. This highlights the importance of including factors at the node and structural network level whilst investigating the importance of proximity. In this case, triadic closure, representing one of the processes that operate at the structural network level, was found to drive tie formation, whereas proximity was not. Hence, factors at the structural network level might offset the effect of being proximate to one another. These findings contribute to the emergent literature into what drives the formation of inter-organizational knowledge exchange ties.

The third question is whether intra-industry mergers and acquisitions (M&As) can offer an alternative or complementary explanation to Marshall-Arrow-Romer (MAR) externalities as to why industries cluster spatially. These agglomeration externalities and M&A activities are two other mechanisms in addition to inter-organizational networks that link organizations and their activities together. Many studies in the agglomeration economies literature have investigated the effect of being co-located with firms in the same industry, possibly inducing knowledge spillovers reflecting MAR-externalities. Yet, no research has compared their effect to the knowledge infusion from firms in the same industry due to M&As. Using data on the Dutch banking industry between 1850 and 1993, which has increasingly clustered in Amsterdam during this time, it is found that the acquisition of firms within the same industry decreases the chance to exit through failure or industry switching. Hence, the acquisition of similar capabilities increases the chance of survival in the same industry. At the same time, co-location with firms in the same industry is found to have a negative effect on survival. Hence, no evidence is found for MAR-externalities. Instead, the spatial clustering of the banking industry in Amsterdam is explained by M&As and the accumulation of M&A experience within banks in Amsterdam over a century. These findings provide new insights into why economic activities agglomerate.

The fourth question is how structural change, at the regional and organizational level, unfolds from economic behavior at the micro level. The evolutionary logic implies that new activities tend to grow out of existing activities because new activities often emerge from the re-combination of existing local capabilities. Recent studies have found evidence of this Penrosian process of related diversification at the country level (Hidalgo et al., 2007) and regional level (Neffke et al., 2011; Boschma et al., 2013; Rigby, 2013; Boschma et al., 2015; Essletzbicher, 2015). None, however, have investigated which agents induce related as well as unrelated growth paths, or structural change, in regions, which is the contribution of Chapter 5. Using Swedish data between 1994 and 2010, evidence is found for the evolutionary idea that change is induced by sources from the outside: entrepreneurs and expanding firms from elsewhere are found to be the agents of structural change in regions. They foster the growth of local activities that require capabilities that are different from the capability base of the regions they enter. In doing so, they help knowledge diffuse between regions, as the activities they set up are much better embedded in the capability base of the regions they come from. At the same time, it is found that expanding firms from elsewhere are as important, if not more important, than entrepreneurs in fostering structural change, which questions the Schumpeterian idea in some of the evolutionary literature that entrepreneurs are the main drivers of structural change. Hence, whereas recent literature has investigated how structural change of local economies unfolds at the macro level, Chapter 5 provides micro insights into this process, highlighting the important role of non-local entrepreneurs and expanding firms in inducing structural change by infusing regions with new capabilities from elsewhere.

Chapter 6 aims to provide micro insights into change and renewal as well, by, instead of the regional level, investigating the agents of change at the plant level. At the macro level, much evidence exists on how plants diversify, often mimicking related diversification following Penrose (1959). Much less is known about how this unfolds at the micro level, which Foss (2011) referred to as so far being “largely an unfilled promise”. Who are the agents that foster plant diversification? Using the same Swedish matched employer-employee data between 1994 and 2010 as in Chapter 5, causal evidence is found that, similar to Chapter 5, change tends to be induced from the outside. Plants are much more likely to switch activities when they have recruited new top managers or top technicians with capabilities that are unrelated the main activity of the plant. When doing so, plants tend to switch to activities that are related to their existing activities as well as the capabilities of the new employee. This reflects the importance of an influx of new capabilities in allowing plant-internal re-combination of existing and new capabilities, which, as evolutionary theory predicts, fosters the development of new activities. Hence, whereas expanding firms and entrepreneurs diffuse knowledge between and induce change within regions, the mobility of top managers and top technicians induces knowledge transfer between and structural change within organizations. These findings provide insights at the micro level into how diversification unfolds, contributing to the existing literature which has investigated regional and plant diversification mainly at the macro level.

7.2 Limitations and future research

7.2.1 Relatedness and knowledge transfer

A key avenue for future research is to further explore the effect of inter-industry relatedness on growth and structural change. Evolutionary reasoning suggests that organizations employing unrelated activities do not benefit and learn from one another because they cannot understand one, which is why relatedness is important. At the same time, if one can link unrelated activities, this could possibly lead to more radical innovations. Fleming (2001) found evidence of this at the firm level. At the regional level, Castaldi et al. (2015) found that whereas related variety supports innovation in general, unrelated variety tends to foster breakthrough innovations. A key question then is what fosters the ability to link unrelated activities.

Possibly regions and organizations need both related and unrelated variety to establish such links. If one conceives industries as a network in which links represent the degree of relatedness between industries (e.g. Hidalgo et al., 2007; Neffke et al. 2011), industries are unable to ‘connect’ to most other industries directly as they employ unrelated activities. However, they might be able to connect to unrelated industries when there are intermediate industries present that bridge them. Related activities would then effectively link unrelated activities. Such cross-industrial exchange of knowledge through shortcuts and possibly multiple paths might induce what Frenken et al. (2012) refer to as recombinant innovations. Key in this are the activities that serve as brokers between unrelated activities. Due to cross-specialization, they might be the most likely facilitators of knowledge spillovers and innovation (Janssen, 2015). Thus, it might be beneficial to have industrial compositions within organizations and regions that contain unrelated activities that are indirectly linked to one another through related activities, which might foster an ecosystem of effective knowledge diffusion between related and unrelated activities.

In adopting such a network approach, it is fruitful to further link the diversification and relatedness literature to the network literature, particularly related to organizational networks. A huge literature exists on how inter-firm networks affect innovation, for instance through being present in networks with sparse structures (Granovetter, 1973), structural holes (Burt, 1992), high cohesion (Walker et al., 1997) and high hierarchy and assortativity (Crespo et al., 2013). With respect to relatedness, Gilsing et al. (2008) investigate how network density and a firm's network centrality impact the effect of relatedness on innovation, finding that there are strong interaction effects at play between them. Thus, they conclude that one needs to investigate the network composition and relatedness jointly to better understand their impact. Such a network approach is promising to adopt at the level of activities and to investigate how the network composition of activities within firms and regions, and changes within those compositions over time, affect structural change.

Furthermore, it is worth exploring the relative importance of relatedness in different forms of knowledge transfer mechanisms between organizations. This PhD thesis has explicitly investigated inter-organizational networks, labor mobility and M&As as knowledge transfer mechanisms, all of which differ from an evolutionary point of view. Because employees accumulate capabilities at work that are embodied within the person and hard to codify and exchange (Almeida and Kogut, 1999; Maskell and Malmberg, 1999), labor mobility is more likely to facilitate the transfer of tacit knowledge than inter-organizational networks. M&As, in turn, facilitate not only the transfer of capabilities at the person level, but also what Nelson and Winter (1982) call the routines that exist at the level of the organization. Thus, because knowledge at a 'deeper level' can be obtained with M&As, relatedness might be more important in this type of mechanism than in the other mechanisms to reap knowledge transfer benefits.

Finally, this PhD thesis has focused on relatedness as linking activities through overlapping knowledge bases and associated synergies. However, activities might also be related in other ways than being cognitively related, particularly by being complimentary. For instance, the tourism industry has been credited with creating extra value by linking to cognitively unrelated but complementary sectors such as design and agricultural activities (Harmaakorpi et al., 2011). To produce new products, firms might require technologies that are cognitively different but that need to be used in conjunction (Breschi et al., 2003). A general purpose technology, in particular, might be complementary to many other technologies. Also, workers and teams in plants derive synergies not only from being cognitively related and learning from one another, but also from complementing one another (Neffke, 2015). It is worth further exploring how such synergies emerge in compositions of activities that are not necessarily related in a cognitive way but are related in a complementary way.

7.2.2 Measuring relatedness and capabilities

A key challenge is measuring relatedness between different activities. This PhD thesis relies on the Standard Industrial Classification (SIC) in Chapter 2 and a measure based on excessive labor flows between industries in chapters 5 and 6. The latter arguably measures relatedness more accurately since there is less theoretical justification that the nested hierarchy of standard industrial classifications reflects economies of scope across industries. At the same time, by using labor flows to measure relatedness one particularly measures relatedness in human capital, whereas industries might also be related through other resources. As an alternative, one could use outcome-based or 'revealed relatedness' measures that focus on the co-occurrence of activities in portfolios, for instance in the industrial portfolios of plants, firms and countries (Teece et al., 1994; Hidalgo, 2007; Bryce and Winter, 2009, Neffke et al. 2011). However, one then assumes that such portfolios are generally related, which disregards unrelated diversification strategies, and one is then also unable to identify the source of relatedness. Future research could shed more light onto these issues by combining these different ways of measuring relatedness and by assessing the extent to which they correlate with one another, as well as the extent to which they are able to predict economic outcomes such as diversification.

Secondly, a key question is if, and how, to incorporate relatedness into measuring renewal within regions, firms and plants. This PhD thesis has made an explicit distinction between industrial change and structural change. Classic work on structural change has defined structural change as change in compositions of the activities of economies (Pasinetti 1981; Paci and Pigliaru, 1997; Fagerberg, 2000). Instead, this PhD thesis has defined structural change as diversification into activities that also require new capabilities, measured by using a degree of inter-activity relatedness as set out above. The advantage of using an inter-industry relatedness measure is that it provides an estimate of capability similarity between all the activities that are distinguished, which is necessary to measure structural change of compositions of activities. However, capabilities themselves are then not measured directly. At the same time, a huge literature exists that explicitly aims to do so, particularly by measuring capabilities at the national level (an overview is given in Fagerberg et al. 2010) and the organizational level (overviews are given in Dosi et al., 2008; Stefano et al., 2010; Teece, 2014). It is worthwhile for future research to link and compare the outcomes of both approaches, which would help into gaining deeper insight into which capabilities link which activities together.

7.2.3 Causality of the effect of relatedness and knowledge transfer on growth and structural change

Another key challenge is to identify the causal effect of relatedness and knowledge transfer on change and renewal. This is especially important within a framework that derives outcomes from economic behaviour at the micro level, thus from behaviour of agents that make choices. Certain strands of the literature, such as neoclassical economics, build models based on the assumption that agents make optimal choices. In the evolutionary literature, in which relatedness and knowledge transfer are key concepts, agents are not assumed to make optimal choices. Yet, they do still make choices based on the information that they possess, but under the assumption of bounded rationality. Thus, from an evolutionary point of view, choices are not optimal but not fully random either. Hence, it is important to consider possible endogeniety issues.

This concerns all chapters of this PhD thesis. Plants do not randomly move between regions, do not randomly hire new employees, and firms do not randomly acquire other firms. Hence, the effect of relatedness and knowledge transfer might, in theory, also reflect the effect of omitted variables. For instance, the hiring of an unrelated employee might simply reflect the fact that a plant is pursuing a strategy of unrelated diversification. If so, the correlation between hiring an unrelated employee and unrelated diversification does not reflect the effect of the unrelated employee coming into the plant as such, but rather reflects the plant's strategy that affects both the hiring decision and the diversification move.

Such endogeneity problems can be dealt with using an identification strategy, but this is not always feasible. Chapter 2 relies on a System-GMM estimator to estimate a causal impact of the relatedness among local industries on regional growth. This estimator uses lagged levels as instruments for first differences, and vice versa. A concern, however, is whether such lags are truly exogenous, especially from an evolutionary perspective that views changes over time as path dependent. Chapter 6 develops an identification strategy based on the death or permanent emigration of an existing employee in a plant on the one hand, and a supply shift instrument in local skill availability to predict what kind of human capital is hired as a replacement on the other hand. Although the exogeneity assumption is plausible here, one could still question whether these events are truly exogenous. For instance, if managers pass away as a result of psychological stress related to pursuing an unrelated diversification strategy, omitted variable effects would still exist. At the same time, it is very hard to identify exogenous variation in characteristics of M&As as investigated in Chapter 4.

These questions highlight the difficulty of identifying a causal effect of relatedness and knowledge transfer on growth and renewal. On the one hand, giving up one's research because one has no (perfect) identification strategy is undesirable as correlations, which might still exist because of an underlying causality, are still informative, especially when they relate to research questions that have not been investigated before. At the same time, it is worth pursuing the effort of identifying causal effects. This trade-off at times causes friction between neoclassical and evolutionary approaches. Increasing attention for this trade-off exists in the development economies literature on economic growth (Rodrik, 2009; Deaton, 2010; Imbens, 2010; 2014). In the context of economic growth, identification of causal effects almost always relies on experiments, particularly randomized controlled trials, or 'natural experiments', Deaton (2010) writes that "experiments have no special ability to produce more credible knowledge than other methods", whereas Imbens (2010) writes that "Deaton is both formally wrong and wrong in spirit. Randomized experiments do occupy a special place in the hierarchy of evidence, namely at the very top." Such a debate might also be fruitful in future research on relatedness, knowledge transfer mechanisms and economic growth and renewal, especially when the micro level of choice-making agents is concerned.

7.2.4 Institutions

Another area of future research is the role of institutions in conditioning the impact of relatedness and knowledge transfer mechanisms on growth and structural change. Effective knowledge transfer is more likely in environments with institutions that facilitate inter-organizational linkages and knowledge sharing (Cooke and Morgan, 1998; Crescenzi et al., 2007; Rodríguez-Pose and Crescenzi, 2008; Rodríguez-Pose, 2013; Fitjar and Rodríguez-Pose, 2015). From an evolutionary point of view, Nelson (1995) argued that institutions co-evolve with markets and technologies. They might foster the introduction of new activities, as well as prevent them due to inertia and institutional hysteresis (Grabher, 1993; Hassink, 2005). In this respect, formal and informal institutions at the national and regional level can be distinguished, as well as institutional agents at the micro level.

First, formal institutions are what North (1990) calls the "humanly devised constraints that shape human interaction", such as property rights and other regulations. Rodríguez-Pose and Di Cataldo (2015) find that quality of government strongly affects the innovative performance of European regions and conclude that certain forms of governments represent a "fundamental barrier" to exploiting the innovation potential of peripheral regions in Europe. Regarding diversification, knowledge transfer is constrained by strong labor market regulations that limit the job mobility of people, as well as legal obstacles to introducing new products and regulations that make it harder for firms to gain access to credit by financial institutions and venture capitalists. Such regulations might provide incentives for firms to only renew themselves incrementally. As such, Boschma and Capone (2015) find that in 'coordinated market economies' there is more related diversification and less unrelated diversification than in 'liberal market economies'.

Second, relatedness and knowledge transfer are affected by informal institutions. They are usually associated with trust and social capital (Putnam, 1993; Knack and Keefer, 1997). First, trust reduces transaction costs (Fukuyama, 1995), which facilitates the exchange of knowledge between firms and plants, particularly in geographical proximity through face-to-face contact (Storper and Venables, 2004). Trust has also been argued to promote entrepreneurship and the functioning of labor markets (Adler, 2001). Second, social capital, which includes norms, social conventions, informal networks and so on (Rodríguez-Pose and Storper, 2006), might facilitate certain types of knowledge diffusion and change. For instance, it might be that bonding social capital allows economies to retain their existing specializations as well as diversify into new activities, whereas bridging social capital only allows economies to diversify (Cortinovis et al., 2015). Hence, formal institutions and informal institutions condition the role of relatedness and knowledge transfer between organizations and their impact on renewal. A key question for future research is the extent to which different types of agents, for instance expanding firms versus entrepreneurs, are affected by those institutions.

At the same time, a key challenge is to investigate institutions from a micro perspective when investigating relatedness, knowledge transfer and renewal. This PhD thesis has investigated agents in the form of firms and workers, but there are also institutional agents. As institutions tend to co-evolve with industries, they might at some point, suffer from hysteresis or 'lock-in', preventing renewal. For instance, Murmann (2003) found that pre-existing regulations regarding patents and university-industry collaborations in the nineteenth century prevented the synthetic dye industry from emerging in countries other than Germany. The same could be said of regulations in 2015 in countries across Europe that stifle activities that apply digital innovations that facilitate the sharing of resources (such as Airbnb). A key question, then, is which agents tend to reinforce existing institutions and which agents tend to change and renew them. A growing literature on 'institutional entrepreneurship' exists which focuses on the agents that are best able to induce institutional change that makes new activities possible (Maguire et al., 2004; Garud et al., 2007; Bathelt and Glückler, 2014). Such agents need to be able to mobilize resources (DiMaggio, 1988). For this, they require capabilities such as political, analytical and cultural skills (Perkmann and Spicer, 2007). It may be that a new influx of such capabilities from elsewhere is required for institutional change, similar to the findings in this PhD thesis on renewal within plants and regions. At the same time, a certain degree of relatedness to existing activities might be required for institutional agents to be able to identify feasible new growth paths. Their impact might also depend on the mechanism through which they interact and exchange knowledge with other agents. Analysing institutions this way from a micro perspective, in conjunction with analyses at the micro level of firms and employees, might yield answers to these questions. This would provide a much broader perspective on how relatedness and knowledge transfer foster growth and structural change of local economies and organizations.

7.2.5 Policy implications

Given the decline of specialized regions, particularly since the global financial crisis of 2008, there has been increasing interest among policy makers in how to foster structural change of local economies. For instance, the European Union's smart specialization agenda on regional development outlines that "smart specialization seeks robust and transparent means for nominating those new activities, at regional level, that aim at exploring and discovering new technological and market opportunities and at opening thereby new domains for constructing regional competitive advantages." (Foray and Goenaga, 2013, p. 1). Haussman and Rodrik (2003) and Rodrik (2004) argue that there are market failures that may prevent such structural change from happening. First, entrepreneurial discovery of new activities might be hampered because the returns to the searching of and experimenting with new activities cannot be fully appropriated due to spillovers and imitation by others. Second, new activities might require large-scale investments in the environment they are embedded in which are not naturally provided by the private sector. Because of these information and coordination externalities, there is a role for policy makers in fostering structural change of economies.

This PhD thesis may inform policy makers on structural change in two ways. First, it highlights the importance of relatedness and knowledge transfer, through the mobility of firms and people, in inducing such structural change. This may be a rationale for policy makers to remove barriers to the mobility of workers and firms, between regions as well as between firms. Second, it provides an empirical framework to measure the extent to which the mobility of a certain activity induces structural changes of a local economy. This could help policy makers in identifying which activities to support and which not to support, depending on what they want to achieve (e.g. related versus unrelated diversification).

At the same time, one has to be careful in deriving policy implications from the findings in this PhD thesis. It has not investigated the effect of policy measures as such, hence it cannot say anything about the effect of specific policy measures. Studies that do so are more informative in this respect. For instance, Mazzucato (2013) extensively investigated how public policy, by what she refers to as the “entrepreneurial state”, has influenced the development of new activities across countries. Moretti et al. (2014) investigated the economic effects of one of the United States’ largest regional development programs, the Tennessee Valley Authority, finding that it has substantially increased manufacturing productivity in the long run. Such evaluation studies have not been conducted yet with respect to public policies concerning relatedness, knowledge transfer and structural change. However, they are necessary to policy makers to evaluate what might happen in the absence of public policy. The smart specialization programmes of the EU, which are now being implemented across many regions in Europe (McCann and Ortega-Argilés, 2015), relate very closely to these topics, and may therefore serve as a fertile breeding ground for future research on public policy effectiveness in these areas.

Furthermore, this PhD thesis has investigated Sweden, Finland and The Netherlands, all of which are advanced economies, whereas knowledge transfer and structural change are more important in less-advanced countries. Some of these countries might be stuck at ‘dead ends’ with the activities and capabilities they currently host (Hidalgo et al., 2007). They would benefit most from an influx of new capabilities to diversify into new activities. Evidence from advanced economies suggests that new influx through foreign direct investment might raise the productivity of domestic firms (Haskel et al., 2007; Crescenzi et al., 2015), particularly through labor mobility as a channel of knowledge transfer between foreign and domestic companies (Balsvik, 2011). A key question is when, and how, such transfer of knowledge is beneficial in less-advanced countries. In uncovering this, promising is the increasing availability of social security, chamber of commerce and tax registry data from these countries to researchers, for instance in Colombia and Mexico. These data allow one to gain a much deeper understanding of the productive structure of these countries, as well as regional variation in the quality of their institutions (e.g. Acemoglu et al., 2015), which provides exciting avenues for future research on relatedness, knowledge transfer and structural change.

8.
Samenvatting in Nederlands

Introductie

Veel regio's in de wereld zijn sterk gespecialiseerd. Bekende voorbeelden zijn Silicon Valley dat gespecialiseerd is in het produceren van computer-gerelateerde producten en Wenzhou in China dat gespecialiseerd is in het produceren van aanstekers. Zij lopen het gevaar in verval te raken als de vraag naar hun producten afneemt. Tekenend is het voorbeeld van Detroit dat gespecialiseerd is in het produceren van auto's. In het midden van de 20e eeuw was dit nog een welvarende stad maar in 2013 haalde de stad internationaal het nieuws toen zij failliet ging. Het bankroet was het grootste in de geschiedenis van de Verenigde Staten.

Om zulke economische neergang tegen te gaan is het van belang dat er nieuwe activiteiten in regio's ontwikkeld worden. Dit is echter niet vanzelfsprekend. Onderzoek laat in toenemende mate zien dat de diversificatie van economieën stapsgewijs verloopt door de ontwikkeling van activiteiten die gerelateerd zijn aan bestaande activiteiten (Hidalgo et al., 2007; Neffke et al., 2011; Boschma et al., 2012). Dit komt omdat bestaande capaciteiten worden hergebruikt in nieuwe activiteiten. Bedrijven functioneren op basis van routines die zich door de tijd heen ontwikkelen. Deze routines zijn niet alleen cumulatief maar ook moeilijk te imiteren door andere ondernemingen vanwege de 'stilzwijgende kennis' die ze bevatten (Nelson en Winter, 1982). Autoproducenten zijn bijvoorbeeld beter in staat om te diversificeren in motorfietsen dan graanproducenten. Ze zijn ook eerder geneigd dit te doen vanwege de fundamentele onzekerheden waarmee zij worden geconfronteerd. Hierdoor zoeken zij naar nieuwe activiteiten waarin hun bestaande capaciteiten hergebruikt kunnen worden.

Voor diversificatie en structurele verandering is het daarom van belang dat er een instroom van nieuwe routines en capaciteiten in regio's en bedrijven gegenereerd wordt. Het is daarom belangrijk inzicht te krijgen in de mechanismen die routines en capaciteiten overdragen. Routines en capaciteiten verspreiden zich niet automatisch door de 'stilzwijgende kennis' die ze bevatten. Dit is kennis die niet op papier is vast te leggen. Daarom verspreiden routines en capaciteiten zich door de entiteiten waarin zij zijn ingebed. Dit zijn in het bijzonder spillovers, spin-offs, arbeidsmobiliteit, fusies en overnames, en bedrijfsnetwerken. Dit proefschrift onderzoekt hoe deze mechanismen de groei en structurele verandering van lokale economieën en bedrijven bevorderen. Het centrale thema is de samenstelling van activiteiten binnen regio's en bedrijven. In hoeverre zijn deze samenstellingen coherent in de zin dat ze bestaan uit activiteiten die vergelijkbare capaciteiten gebruiken? Hoe worden activiteiten met elkaar verbonden en hoe zijn portfolio's van activiteiten van invloed op groei? En hoe ontstaan nieuwe activiteiten binnen bestaande portfolio's? Dit proefschrift onderzoekt deze vragen door het beantwoorden van 5 onderzoeksvragen in 5 hoofdstukken.

Onderzoeksvraag hoofdstuk 2: In hoeverre wordt de invloed van related variety op regionale werkgelegenheidsgroei geconditioneerd door de technologische intensiteit van lokale industrieën?

Een kernvraag binnen de literatuur over agglomeratievoordelen is hoe de samenstelling van activiteiten binnen regio's van invloed is op regionale groei. Frenken et al. (2007) maakten expliciet het onderscheid tussen diversiteit van gerelateerde activiteiten en diversiteit van niet-gerelateerde activiteiten in regio's. Zij toonden aan dat een samenstelling van gerelateerde industrieën in regio's, of 'related variety', nodig is voor regionale werkgelegenheidsgroei. Zij stellen dat dit komt omdat er dan noch te veel cognitieve overlap is tussen lokale activiteiten (waardoor men weinig van elkaar kan leren) noch te weinig cognitieve overlap (waarin leren wordt belemmerd omdat het moeilijker is elkaar te begrijpen). Hoofdstuk 2 onderzoekt of de technologische intensiteit van lokale sectoren de invloed van related variety op regionale groei conditioneert. Andere onderzoekers (Heidenreich 2009; Kirner et al. 2009; Santamaria et al. 2009) hebben betoogd dat kennisspillovers, leren en productinnovaties vooral relevant zijn voor hightech sectoren. Deze industrieën werken met complexe kennis en zijn met name gericht op radicale innovaties (Antonelli, 2004). Daarom zijn zij in het bijzonder afhankelijk van inter-industriële spillovers en leereffecten en daarom is de verwachting dat zij het meest profiteren van related variety.

Dit wordt onderzocht voor regionale werkgelegenheidsgroei in Finland tussen 1993 en 2006, een periode waarin de economie van Finland veranderde in een hightech economie met een toenemende variatie van hightech sectoren. Dynamische panel regressies met System GMM schatters tegen endogeniteitsproblemen worden gebruikt om te testen of het effect van related variety van hightech sectoren op regionale groei in Finland verschilt van het effect van related variety van low-en- medium-tech sectoren.

Uit de resultaten blijkt dat related variety op zich geen invloed heeft op regionale werkgelegenheidsgroei. In plaats daarvan heeft alleen related variety van hightech sectoren een positieve invloed. Het is daarom belangrijk de technologische intensiteit van lokale sectoren in acht te nemen als het gaat om de invloed van related variety op regionale werkgelegenheidsgroei.

Onderzoeksvraag hoofdstuk 3: Wat bepaalt de creatie van kennisoverdrachtbanden tussen organisaties?

Om de samenstelling van de activiteiten binnen regio's en bijbehorende kennisoverdrachteffecten beter te begrijpen, is het belangrijk inzicht te verkrijgen in hoe banden tussen organisaties tot stand komen en hoe deze veranderen door de tijd heen. Dit vereist dat men het belang van factoren op dyad niveau (link niveau – kenmerken van de relatie zelf) onderzoekt, met name gerelateerdheid en andere vormen van nabijheid, in combinatie met factoren op het bedrijfsniveau (bijvoorbeeld absorptievermogen) en structurele netwerkniveau. Dit laatste verwijst naar factoren van de bestaande structuur van het netwerk die het ontstaan van toekomstige netwerkbanden beïnvloeden. Triadic closure bijvoorbeeld houdt in dat partners van een organisatie sneller geneigd om onderling ook met elkaar een band aan te gaan en partners te worden. Er is dan sprake van een zelfversterkend en pad afhankelijk proces dat de bestaande netwerkstructuur versterkt (Nelson, 2002). Zulke processen kunnen het belang van factoren op dyad niveau, zoals gerelateerdheid aan elkaar in cognitief opzicht, verminderen.

Om dit te onderzoeken worden netwerk gegevens gebruikt over technologische kennisuitwisseling tussen Nederlandse luchtvaartorganisaties in 2008. Deze gegevens zijn verzameld door semigestructureerde interviews met leden van de Nederland Aerospace Group (NAG). Zij genereren 95% van de totale omzet door Nederlanders luchtvaartorganisaties (NAG, 2008). Het netwerk tussen hen wordt geanalyseerd met exponential random graph models. Dit zijn nieuwe netwerk analyse technieken die zijn ontwikkeld in de wiskundige sociologie (Snijders et al. 2006;. Robins et al., 2006, 2007; Wang et al., 2012) en steeds meer gebruikt worden door verschillende wetenschappelijke disciplines. Dit komt omdat zij een onderzoeker in staat stellen het belang van factoren op dyad niveau te bepalen in combinatie met factoren op het bedrijfsniveau en structurele netwerkniveau.

Uit de resultaten blijkt dat het aangaan van netwerkbanden gedreven wordt door geografische nabijheid, institutionele nabijheid en triadic closure. Als alleen nabijheid variabelen worden opgenomen, levert dat modellen op die niet goed het waargenomen netwerk voorspellen. Dit benadrukt het belang van het opnemen van factoren op het structurele netwerkniveau in onderzoek naar het belang van nabijheid in netwerken. In dit geval blijkt triadic closure de kans op het aangaan van baanden te versterken, in tegenstelling tot het aan elkaar gerelateerd zijn in cognitief opzicht.

Onderzoeksvraag hoofdstuk 4: In hoeverre verhogen fusies en overnames van bedrijven in dezelfde industrie de prestaties van bedrijven? Hoe verhoudt dit effect zich tot het effect van co-locatie met bedrijven uit dezelfde industrie? En in hoeverre zorgen fusies en overnames binnen dezelfde industrie voor de ruimtelijke concentratie van een industrie door de tijd heen?

Naast bedrijfsnetwerken worden organisaties en hun activiteiten met elkaar verbonden door fusies en overnames (mergers en acquisitions, c.q. M&As) en kennisspillovereffecten. De verwachting is dat, zoals besproken in Hoofdstuk 2, de co-locatie met soortgelijke activiteiten geen leereffecten oplevert. Veel studies zijn gedaan over het bestaan van zulke Marshall-Arrow-Romer (MAR) externaliteiten, maar het effect van kennisspillovers tezamen met M&As is nog niet onderzocht. De hypothese is dat M&As belangrijker zijn dan MAR externaliteiten in het verhogen van de prestaties van organisaties, waardoor het juist M&As zijn die de ruimtelijke concentratie van een industrie bevorderen. Zowel M&As binnen dezelfde industrie als spillovers uit dezelfde industrie voegen capaciteiten uit gemeenschappelijke activiteiten toe aan bedrijven. Hierdoor worden bestaande capaciteiten mogelijk versterkt waardoor de kans op diversificatie in nieuwe activiteiten afneemt. MAR-externaliteiten omvatten echter ook concurrentie effecten van lokale bedrijven, bijvoorbeeld door een toenemende vraag naar dezelfde lokale bronnen. Bovendien geven M&As, doordat een hele bedrijfsstructuur wordt overgenomen, bedrijven toegang tot de routines van een organisatie (Nelson en Winter, 1982). Dit kan de implementatie van extern verworven vaardigheden versoepelen. Daarom is de verwachting dat niet zozeer MAR-externaliteiten maar juist M&As de ruimtelijke concentratie van een industrie door de tijd heen bevorderen.

Dit wordt onderzocht voor de bankensector in Nederland tussen 1850 en 1993. Tijdens deze periode concentreerde de bankensector zich in toenemende mate in Amsterdam. Voor de banken in deze periode is de locatie van het hoofdkantoor, alsmede het jaar van oprichting en uittreding bekend. Ook is bekend of uittredingen gebeuren door fusies met of overnames van andere banken. Met deze data kunnen de prestaties van banken, gemeten met hun overlevingskans, worden geanalyseerd, alsmede de ruimtelijke evolutie van de banksector over een tijdsbestek van meer dan 100 jaar.

Uit de resultaten blijkt dat M&As een belangrijke rol hebben gespeeld in de ruimtelijke concentratie van het Nederlandse bankwezen in Amsterdam gedurende de twintigste eeuw. Banken in Amsterdam waren zeer actief in het overnemen van andere banken, zowel in Amsterdam als erbuiten. M&A ervaring, daaropvolgend, verlaagde de kans om uit te treden. Tegelijkertijd verhoogde het aanwezig zijn in Amsterdam op zich de kans om uit te treden. Dit betekent dat de ruimtelijke concentratie van het Nederlandse bankwezen niet zozeer werd veroorzaakt door het feit dat banken gemiddeld beter presteerden omdat ze in Amsterdam gevestigd waren – er is dus geen aanwijzing van MAR-externaliteiten of een 'positief Amsterdam effect' voor de bankensector. In plaats daarvan namen banken in Amsterdam een groot deel van banken elders in Nederland over. Het vergaren van ervaring in het doen van M&As vond voornamelijk plaats in Amsterdam, wat weer een positieve invloed had op de overlevingskansen van de banken daar, met een toenemende mate van ruimtelijke concentratie van het bankenwezen in Amsterdam als gevolg.

Onderzoeksvraag hoofdstuk 5: Wie zijn de belangrijkste drijvers van structurele verandering in een regio?

Waar de vorige hoofdstukken onderzocht hebben hoe de regionale samenstelling van activiteiten tot stand komt en wat de invloed ervan is op prestaties van de organisatie, onderzoekt hoofdstuk 5 welke actoren de regionale samenstelling van activiteiten veranderen. Onderzoek wijst in toenemende mate uit dat economieën diversificeren in gerelateerde activiteiten (Neffke et al. 2011;. Hidalgo et al., 2007). Er is echter nog geen systematisch bewijs voor welke actoren economieën diversificeren: welke actoren zorgen voor specialisatie en gerelateerde diversificatie en welke actoren zorgen voor ongerelateerde diversificatie en structurele verandering? Schumpeteriaanse theorieën beschouwen ondernemers als de belangrijkste drijvers van verandering. Daarnaast stellen evolutionaire redeneringen dat verandering van binnenuit onwaarschijnlijk is. De hypothese is daarom dat voor structurele verandering instroom van buiten nodig is, met name van ondernemers.

Dit wordt onderzocht met Zweedse belastingdata van alle werknemers en bedrijven tussen 1994 en 2010. Hieruit worden bestaande vestigingen en nieuwe vestigingen van bestaande bedrijven en ondernemers onderscheiden, alsmede of men van binnen of buiten de regio komt. De gerelateerdheid tussen sectoren wordt gemeten met jaarlijkse arbeidsstromen tussen industrieën. Deze industrie-industrie matrix wordt gebruikt om structurele verandering te onderscheiden van industriële verandering. Eerder onderzoek definieert structurele verandering als een wijziging in de activiteitenmix van een economie (bijvoorbeeld Pasinetti, 1981; Paci en Pigliaru, 1997; Fagerberg, 2000). Vanuit evolutionair perspectief echter, waarin de routines en capaciteiten van bedrijven expliciet worden onderscheiden van hun activiteiten, betekent een verandering in de activiteitenmix niet per definitie structurele verandering. Een verschuiving in de specialisatie van een regio van het maken van schoenen naar het maken van laarzen zou een verandering in de mix van activiteiten vormen, maar geen structurele verandering. Dit komt omdat beide activiteiten dezelfde capaciteiten gebruiken – zij zijn sterk gerelateerd aan elkaar.

Uit de resultaten blijkt dat structurele verandering wordt veroorzaakt door actoren van buitenaf: ondernemers en expanderende bedrijven van elders zijn de voornaamste drijvers achter structurele verandering in regio's. Zij bevorderen de groei van activiteiten die andere capaciteiten nodig hebben dan die van bestaande activiteiten in regio's. In dit proces bevorderen ze de verspreiding van kennis tussen regio's aangezien de activiteiten die zij opzetten veel beter ingebed zijn – qua capaciteiten - in de regio waar ze vandaan komen. Tegelijkertijd blijkt dat uitbreidende bedrijven even belangrijk, zo niet belangrijker, zijn dan ondernemers in het bevorderen van structurele verandering. Dit zet vraagtekens bij de Schumpeteriaanse notie in een deel van de literatuur dat ondernemers de belangrijkste aanjagers van structurele verandering zijn.

Onderzoeksvraag hoofdstuk 6: Wat is de invloed van de rekrutering van nieuwe topmanagers en toptechnici in bedrijfsvestigingen op diversificatie?

Waar hoofdstuk 5 de drijvers van structurele verandering op regionaal niveau onderzoekt, onderzoekt hoofdstuk 6 hoe diversificatie op organisatieniveau plaatsvindt. Er is veel bekend over diversificatiepatronen in organisaties maar veel minder is bekend over welke actoren tot wat voor soort diversificatie aanzetten. De hypothese is dat de instroom van nieuwe capaciteiten door arbeidsmobiliteit de kans op diversificatie in nieuwe activiteiten vergroot. Werknemers ontwikkelen capaciteiten op het werk die vaak worden belichaamd in de persoon en moeilijk te codificeren zijn (Almeida en Kogut, 1999; Maskell en Malmberg, 1999). Daarom hevelen ze stilzwijgende kennis over tussen bedrijven als ze van baan veranderen. Het aannemen van nieuwe managers en technici zorgt er daarom voor dat een bedrijfsvestiging capaciteiten verkrijgt die anders moeilijk te verkrijgen zijn. De verwachting is dat hierdoor de kans op diversificatie toeneemt. Dit komt omdat binnen de vestiging recombinatie van bestaande capaciteiten met dee capaciteiten van de nieuwe werknemer mogelijk is, waardoor nieuwe activiteiten mogelijk worden. Daar uit zou volgen dat nieuwe activiteiten zowel de capaciteiten van de huidige activiteiten van de bedrijfsvestiging als die van de nieuwe werknemer weerspiegelen.

Om dit te onderzoeken wordt dezelfde Zweedse belastingdata als in hoofdstuk 5 gebruikt. Een belangrijke empirische uitdaging is een causaal effect van nieuwe werknemers te identificeren, aangezien de instroom van nieuwe werknemers ook een bepaalde bedrijfsstrategie (met name een diversificatiestrategie) kan reflecteren of andere factoren die niet gemeten zijn. Daarom is er een identificatiestrategie toegepast die gebruikt maakt van informatie over de dood of permanente emigratie van een bestaande top manager of toptechneut in een bedrijfsvestiging aan de ene kant en een aanbodverschuivingsinstrument in de beschikbaarheid van menselijk kapitaal in de regio aan de andere kant. De laatste wordt gebruikt om te voorspellen wat voor soort menselijk kapitaal wordt aangenomen.

Uit de resultaten blijkt dat verandering wordt geïnitieerd door nieuwe capaciteiten van buitenaf. De kans om te diversificeren in nieuwe activiteiten stijgt wanneer nieuwe top managers of top technici zijn gerekruteerd met capaciteiten die niet gerelateerd zijn aan de kernactiviteit van de vestiging. Als zij diversificeren, dan is het naar activiteiten waarin zowel de capaciteiten van de huidige activiteiten zijn weerspiegeld als de capaciteiten van de nieuwe werknemer. Dit benadrukt wederom het belang van de instroom van nieuwe capaciteiten wat de interne recombinatie van bestaande en nieuwe capaciteiten mogelijk maakt, wat, zoals de evolutionaire theorie voorspelt, de kans op de ontwikkeling van nieuwe activiteiten verhoogt. Waar uitbreidende bedrijven en ondernemers kennis verspreiden tussen en structurele verandering veroorzaken in regio's, zorgt arbeidsmobiliteit van top managers en toptechnici voor kennisoverdracht tussen en structurele verandering in organisaties.

Toekomstig onderzoek

De bevindingen in dit proefschrift geven een aantal aanknopingspunten voor vervolgonderzoek. Ten eerste is het belangrijk om het effect van gerelateerdheid op groei en structurele verandering verder te onderzoeken. Een mogelijke hypothese is dat industriële composities binnen organisaties en regio's het best functioneren wanneer ongerelateerde activiteiten door middel van gerelateerde activiteiten aan elkaar gekoppeld zijn. Dit kan zorgen voor een effectief ecosysteem van kennisoverdracht tussen gerelateerde en ongerelateerde activiteiten. In deze netwerkbenadering is het noodzakelijk de diversificatie literatuur verder te koppelen aan de netwerk literatuur, met name aan de literatuur over organisatorische netwerken.

Ten tweede heeft dit proefschrift expliciet de mechanismen van kennisoverdracht onderzocht in de vorm van netwerken, arbeidsmobiliteit en M&As. Zij verschillen echter vanuit evolutionair oogpunt. M&As faciliteren niet alleen de overdracht van kennis op persoonsniveau maar ook de overdracht van wat Nelson en Winter (1982) de routines van een organisatie noemen. Omdat kennis op een 'dieper niveau' kan worden verkregen door M&As, speelt gerelateerdheid wellicht een belangrijke rol dan bij de andere mechanismen om te kunnen profiteren van kennisoverdracht.

Ten derde kunnen activiteiten ook op andere manieren dan cognitief aan elkaar gerelateerd zijn. De toeristische sector bijvoorbeeld creëert extra waarde door te linken aan cognitief ongerelateerde maar complementaire sectoren, zoals de ontwerpindustrie en agrarische industrie (Harmaakorpi et al., 2011). Het is de moeite waard verder te onderzoeken hoe structurele verandering plaatsvindt in composities van activiteiten die niet noodzakelijk in cognitieve zin gerelateerd zijn maar wel in complementaire zin.

Ten vierde heeft dit proefschrift structurele verandering gedefinieerd als diversificatie in activiteiten die ook nieuwe capaciteiten gebruiken. Dit is gemeten met een gerelateerdheidsmatrix tussen industrieën gemaakt op basis van de officiële industrieklassificatie alsmede arbeidsstromen tussen industrieën. Het voordeel van zo'n matrix is dat het een schatting van gerelateerdheid geeft tussen alle industrieën, wat noodzakelijk is om structurele verandering in de samenstelling van activiteiten te meten. Echter, capaciteiten zelf zijn niet direct gemeten. Er bestaat echter veel literatuur die wel capaciteiten direct probeert te meten. Het is veelbelovend om vervolgonderzoek verder te koppelen aan die literatuur en methodes die gerelateerdheid en capaciteiten meten in beide benaderingen verder met elkaar te vergelijken.

Ten vijfde is het een belangrijke uitdaging om een causaal effect van gerelateerdheid en kennisoverdracht op verandering en vernieuwing te identificeren. Hoofdstuk 2 is gebaseerd op een System-GGM indicator om het causale effect van related variety op regionale werkgelegenheidsgroei te identificeren. Hoofdstuk 6 ontwikkelt een identificatiestrategie gebaseerd op de dood of permanente emigratie van een bestaande werknemer in een bedrijfsvestiging aan de ene kant en een aanbodverschuivingsinstrument in de beschikbaarheid van menselijk kapitaal in de regio aan de andere kant. Een centrale empirische vraag in deze context is of zulke variabelen echt exogeen zijn en of de identificatiestrategie echt valide is. Aan de ene kant is het niet doen van bepaald onderzoek omdat men geen (perfecte) identificatiestrategie heeft ongewenst. Dit is omdat correlaties ook waardevol kunnen zijn aangezien zij een onderliggende causaliteit kunnen weerspiegelen. Tegelijkertijd is het de moeite waard om causale effecten trachten te identificeren. Steeds meer aandacht voor deze trade-off bestaat in de ontwikkelingseconomische literatuur over economische groei (Rodrik, 2008; Deaton, 2010; Imbens, 2010, 2014). Meer aandacht voor deze trade-off zou ook waardevol zijn in toekomstig onderzoek naar gerelateerdheid, kennisoverdracht en economische groei en structurele verandering, vooral wanneer het om het microniveau gaat van actoren die bewust keuzes maken.

Ten zesde is vervolgonderzoek nodig naar de rol van instituties in het conditioneren van de invloed van gerelateerdheid en kennisoverdracht op groei en structurele verandering. Kennisoverdracht is effectiever in omgevingen met instituties die het aangaan van bedrijfsrelaties en het delen van kennis bevorderen (Cooke en Morgan, 1998;. Crescenzi et al. 2007; Rodriguez-Pose, 2013; Fitjar en Rodriguez-Pose, 2015). Formele en informele instituties kunnen nieuwe activiteiten bevorderen maar ook vermoeilijken door institutionele 'lock-in' (Grabher, 1993; Hassink, 2005). Een belangrijke vraag voor toekomstig onderzoek is de mate waarin verschillende actoren, bijvoorbeeld uitbreidende bedrijven en ondernemers, worden beïnvloed door deze instituties. Ook is het belangrijk om de instituties zelf vanuit micro-perspectief te onderzoeken. Een belangrijke vraag is wat voor soort institutionele agenten neigt om bestaande instituties te versterken en welke soort geneigd is ze te vernieuwen. Een mogelijke hypothese is dat institutionele actoren van buitenaf nodig zijn voor vernieuwing, vergelijkbaar met de bevindingen in dit proefschrift over vernieuwing in bedrijven en regio's.

Ten zevende is verder onderzoek naar beleidsimplicaties waardevol. Er is toenemende belangstelling voor structurele verandering in beleidskringen (zie bijvoorbeeld de Smart Specialization Agenda van de Europese Unie - McCann en Ortega-Argilés, 2015). Dit is met name zo sinds de financiële crisis van 2008 die bepaalde gespecialiseerde regio's hard geraakt heeft. Haussman en Rodrik (2003) en Rodrik (2004) stellen dat er in theorie een rol voor beleidsmakers is weggelegd in het aandrijven van structurele verandering. Dit is vanwege marktfalen gerelateerd aan het zoeken en exploiteren van innovaties en grootschalige investeringen die voor nieuwe activiteiten nodig zijn. Dit proefschrift benadrukt het belang van gerelateerdheid en kennisoverdracht, door de mobiliteit van bedrijven en werknemers, in het aandrijven van structurele verandering. Dit kan een motief zijn voor beleidsmakers om belemmeringen van arbeidsmobiliteit en migratie tussen regio's van bedrijven te verminderen. Ten tweede biedt dit proefschrift een empirisch raamwerk om te meten in hoeverre een nieuwe activiteit structurele verandering van een lokale economie teweegbrengt. Dit kan beleidsmakers helpen bij het bepalen van welke activiteiten te ondersteunen, afhankelijk van het beleidsdoel (bijvoorbeeld gerelateerde versus ongerelateerde diversificatie).

Ten slotte is het veelbelovend om gerelateerdheid, kennisoverdracht en structurele verandering te onderzoeken in andere landen dan Finland, Nederland en Zweden. Sommige landen herbergen activiteiten en capaciteiten waarmee ze weinig kanten op kunnen (Hidalgo et al., 2007). Een instroom van nieuwe capaciteiten, bijvoorbeeld door buitenlandse investeringen, zou hen kunnen helpen te diversificeren in nieuwe activiteiten. Veelbelovend in dit opzicht is de toenemende beschikbaarheid van sociale zekerheid data, kamer-van-koophandel data en belastingdata in deze landen, bijvoorbeeld in Colombia en Mexico. Deze gegevens maken een dieper inzicht mogelijk in de productieve structuur van deze landen alsmede in regionale variatie in de kwaliteit van instituties aldaar (zie bijvoorbeeld Acemoglu et al., 2015). Beide zijn zeer waardevol voor toekomstig onderzoek naar gerelateerdheid, kennisoverdracht en structurele verandering.

R.
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Curriculum Vitae

Matte Hartog was born on 7 November 1987 in Zwolle, The Netherlands. He graduated from the London School of Economics with an MSc degree in Local Economic Development (2010, with merit) and from Utrecht University with an MSc degree in Human Geography and Planning (2010, cum laude). He was awarded a Huygens Talent Scholarship by the Dutch government in 2010 and is the 2010 recipient of the Taught Postgraduate Student Award by the Regional Science Association International, British and Irish Section. In 2011 he started working on his doctoral thesis at Utrecht University. For part of the analysis, he spent numerous months over the years in Sweden as a visiting scholar at Lund University. Matte currently works as a Research Fellow at the Center for International Development at Harvard University.