Related variety and regional development
Insights from Germany

Related variety en regionale ontwikkeling
Inzichten uit Duitsland

(met een samenvatting in het Nederlands)

Proefschrift

ter verkrijging van de graad van doctor
aan de Universiteit Utrecht
op gezag van de rector magnificus, prof.dr. G.J. van der Zwaan,
ingevolge het besluit van het college voor promoties
in het openbaar te verdedigen op
woensdag 21 september 2016 des ochtends te 10.30 uur

door

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geboren op 4 oktober 1981 te Wolfen, Duitsland

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Für Katja, die immer mitgedacht hat.

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Acknowledgements

I am very happy to take the opportunity to thank those people who supported me during this period.

First, my supervisors Ron Boschma, Pierre-Alexandre Balland and Andrea Morrison for their kind understanding, their continuous support and straightforward way to discuss the content of this thesis;

Tom Broekel, with whom I shared and developed many ideas and who has become a friend during this period;

Claus Michelsen, who was already a friend before the start of the thesis, but who has become an even better one.

Mirko, Walter, Alex, Lutz, Eva, Iciar, Micha, Christoph and Jutta for making research at the Halle Institute for Economic Research more than science.

My parents for their patience and enduring support, my brother for his continuous input and for always being there and having an open ear.

Selma and Marta for their beautiful smiles and for making me such a proud father.

And last Katja.

Chapter 1

Introduction

1.1 Heterogeneity, variety and economic development

A central contribution of the evolutionary approach in economics is the concept of heterogeneity. The concept challenged the conventional wisdom of the representative agent (Marshall 1920), prominent in neoclassical approach in economics, and laid the ground for the majority of today's economic modelling. The relevance of heterogeneity for recent economic theory can be highlighted by the words of James Heckman in his Nobel lecture in the year 2000. Herein, he stated that: "The most important discovery [from microeconometric investigations] was the evidence on the pervasiveness of heterogeneity and diversity in economic life" (Heckman, 2001, p. 673). Also Kenneth Arrow (2004, p. 301) adds to this point by arguing that: "One of the things that microeconomics teaches you is that individuals are not alike. […] If we didn't have heterogeneity, there would be no trade." This places heterogeneity of agents and their interactions in economic settings at the heart of economic theory.

Cantner and Hanusch (2005, p. 15) define heterogeneity as a concept "which refers to the degree of [technological] difference within a population of observations […] which differ with respect to their efforts, behaviors and/or success". This broad definition allows addressing heterogeneity from a multitude of perspectives such as the level of observations (e.g. individuals, firms and aggregated entities such as regions), the kind of characteristics they show, the activities these observations undertake (e.g. patterns of production and consumption or directions of innovations) and calls for a connection of these dimensions to relate observation's heterogeneous properties to heterogeneous behaviour (Cantner and Hanusch 2005). To account for heterogeneity, the economics literature has developed different concepts. The thesis will follow Saviotti (1996) who conceptualises heterogeneity as variety, defined by the number of distinguishable actors, activities and objects required to characterise an economic system. This follows a definition of diversity in biology (Pielou 1977) but allows addressing variety economically both from an input and output perspective.

The analysis of the variety of economic agents is of relevance because variety is found to be a fundamental component of the long-term development of economic systems. The generation of new variety requires innovation (Saviotti 1994). This makes variety compatible with Schumpeterian thinking long-term economic development (Schumpeter 1912). Saviotti and Pyka (2004) further demonstrate that an economy that does not increase variety. e.g. in terms of sectors over time, will ultimately stagnate because new sectors are required to absorb labour that has become redundant in pre-existing sectors over the life cycle. Hence, variety shapes the general economic development via the emergence of new activities, old ones that decline, via changing weights of activities and changing patterns of their interplay.

These properties make variety a determinant of future economic development (Saviotti and Pyka 2004). Indeed, it can be shown that the variety of the economic system has grown over time. However, it has also become evident that variety itself is not uniformly distributed across space (Saviotti and Frenken 2008). Using the dynamics of countries' export portfolios Hausmann, Hwang and Rodrik (2007) demonstrate a persistent asymmetry in the distribution of the production capabilities across the world. If this variety of export products would reflect just different combinations in the use of the production factors capital and labour, there would be nothing to worry about. However, Hausmann and Klinger (2006) as well as Hidalgo et al. (2007) show that products differ in the number of near neighbouring products. Having more neighbouring products implies that fewer capabilities are missing when trying to diversify into these new products. This brings the composition of variety on the agenda of economic development and makes it a factor explaining the challenges of productive transformations of economic entities. Assuming that products cannot be made unless the complete set of capabilities is present, the ability to enter into a new product depends on how many capabilities are already present (Hausmann and Hidalgo 2010). Furthermore, this relates variety to the rise of a path-dependent development trajectory where future economic development is conditioned by existing economic structures and capabilities (Saviotti and Frenken 2008).

1.2 Variety, space and proximity of economic agents

The section above started to address the relationship between variety and space at the level of nations. However, already the early works of Jane Jacobs (1969) highlight that the role of variety might be even more important at smaller spatial scales. Contributing to the theory of agglomeration economies Jacobs (1969) argued that cities with a diversified production structure have higher rates of economic growth because spillovers frequently occur across sectors. This was against the literature on industrial specialisation of regions where firms benefit and learn predominately from spillovers within the same sector (Marshall 1920).

The arguments by Jacobs (1969) indicate that the mechanisms through which national resources reallocate between industries are present also at the regional level. Hence, while variety provides the base for different kinds of exchange between economics agents such as trade and interactive learning (Canter and Hanusch 2005), especially the process knowledge generation and diffusion is directed by localised capabilities and facilitated by spatial proximity (Maskell and Malmberg 2007). Indeed, first studies on the relevance of agglomeration economies provided evidence that the variety of geographically proximate industries has a positive effect on regional innovation and growth (Glaeser et al. 1992). However, subsequent research presented only inconclusive evidence on the link between variety, spatial proximity and economic performance (Beaudry and Schiffauerova 2009).

Frenken et al. (2005, p. 22) point out that this "ambiguity in results is probably due, at least in part, to problems of [...] definitions of variety, [...] and spatial and sectoral linkages…". A crucial problem in this discussion rests on the assumption that knowledge will spill over among a variety of agents simply because they are neighbours in space (Boschma and Frenken 2009). Contrary, recent literature suggests that proximity in various dimensions is needed to foster knowledge spillovers. Boschma (2005) emphasises that cognitive, social, institutional and organisational distances need to be overcome when a variety of agents interacts. In particular, the notion of cognitive distance has thereby gained attention in the economic geography literature (Frenken et al. 2007). Given that knowledge development is tacit and cumulative with knowledge being embodied in individuals and firms, variety in the knowledge of economic agents is the rule (Boschma and Frenken 2009). When bringing together these agents with a variety of knowledge and capabilities, they should be able to bridge knowledge gaps. Put differently, their cognitive distance should be close enough to allow mutual understanding but distant enough to enable innovation (Nooteboom 2000).

This means that similar to above, a variety of geographically localised capabilities or assets is neither a necessary nor a sufficient condition for regional development. Rather it is again the specific composition of variety that matters. Especially the cognitive dimension of interactive learning seems to be relevant in this context. This is addressed by the concept of related and unrelated variety (Boschma and Martin 2007). The notion of related variety is supposed to capture 'optimal' degrees of cognitive distance that enable knowledge spillovers and effective knowledge transfer between heterogeneous agents. In addition to that, questions with respect unrelated variety address the role of variety for the long term stability of a regional economy (Essletzbichler 2007). In line with the discussion of Hausmann and colleagues, this makes the composition of variety a factor explaining the challenges of regional productive transformations and gives rise for variety to foster path-dependent regional development conditioned by existing economic structures.

1.3 Related variety and regional development

The concept of related variety is a building block of evolutionary economic geography (EEG). The EEG considers regions to be subject to a never-ending process of creative destruction (Neffke et al. 2011). The basic concern of the EEG is to analyse "*the processes by which the economic landscape – the spatial organization of economic production, distribution and consumption – is transformed over time*." (Boschma and Martin 2007, p. 3). This allows addressing the role of related variety from a spatial perspective, hence, as a force driving regional transformations. Thereby, related variety is understood as a result as well as a driver of the direction and pace of future regional change. This means that relatedness in spatial structures and the place-specific features produced so themselves feedback to drive regional economic evolution (Boschma and Lambooy 1999). Put again in the words of Saviotti and Pyka (2004), in the long run, related and unrelated variety shape regional development through the emergence of new activities and old ones that decline as well as by changing patterns of their interplay.

In theory, economic agents in a region may be related through several channels. One could think about economic agents such as firms or more aggregated industries that are related through regional inputs-output relationships from a value chain perspective (Essletzbichler 2015) or more general of economic agents relying on similar patterns in their intensity of using different production factors such as land, labour and capital (Leamer 1984). Similarly, plant or regional product portfolios might be related through the presence of economies scope (Neffke et al. 2011, Boschma et al. 2013). Regional industries might be related from the perspective of common skill requirements making labour mobility between them more probable (Neffke and Henning 2013). Firms may rely on technologies that originate from a common technology base or may be related because they face similar technological complementarities necessary to advance (Boschma and Frenken 2009). Scientific fields might be more related to each other because they address common questions from different perspectives (Boschma et al. 2014).

These dimensions of relatedness are addressed in the EEG to understand precisely the relationship between the variety of regional agents and long-term regional development. The patterns of relatedness are supposed to govern the ease of how economic entities change their composition as economic agents move preferentially to related objects or activities from a spatial perspective (Boschma et al. 2009). Consequently, this thesis will adopt the concept of related variety and apply it to different aspects of regional and technological development.

1.4 Contribution of the thesis

The contribution of the thesis is to discuss the research on related variety and regional economic development from a more comprehensive perspective on sources of agglomeration economies grounded in the work of Marshall (1920). So far, the relatedness literature has a focus on technological relatedness and cognitive proximity with a strong reliance on patent and industry level data (Frenken et al. 2007, Boschma et al. 2009, Boschma and Iammarino 2009, Boschma and Frenken 2011, Boschma et al. 2012, Boschma et al. 2015). However, this focus on technological and industrial relatedness is too narrow. In theory, the effects of related variety can be assumed to be present across a wide range of economic agents and their activities. Although these dimensions might differ with respect to the channel and magnitude of the effect of relatedness on the dynamics of economic agents, recent EEG literature stresses that related regional economic evolution should work independently of entity or channel studied and measure employed (Essletzbichler 2015).

The first main contribution of the thesis is to widen the existing evidence on the multi-dimensional nature of relatedness with respect to different types of economic agents and activities. First, chapter 2 explores the relevance of the concept of related variety from a combined regional input-output and industrial cluster perspective. This is of importance because input-output linkages are found to be the most important factor in explaining industry agglomeration (Ellison et al. 2010) while industrial clusters represent a dominant target of regional policy action. Second, chapters 3 and 6 contribute to the understanding of how a distinctive occupational perspective may enhance our understanding of the relationship between related variety and regional development. Occupations reflect an important indicator for human capital. Chapter 3 establishes that conceptual progress can be made when the industry perspective in the traditionally related variety concept is widened by exactly this information about the spatial distribution of occupations. Chapter 6 extends the relatedness literature by proposing a direct link between related variety in occupations and regional occupational diversification. This novel approach allows embedding the related variety approach into the literature on regional human capital accumulation. Third, the chapters 4 and 5 adopt the concept of related variety to the perspective of inter-industry R&D efforts. Referring to studies on recombinant innovation (Fleming 2001), the chapters present a project level foundation of search processes of industries for knowledge over time that allows tracing time-varying inter-industry relatedness patterns in research and development. This is in contrast to the identification of relatedness patterns based upon patents reflecting R&D

outputs. Hence, this approach may complement the patent-based analysis of patterns of relatedness by focussing on R&D efforts from an input perspective.

The second main contribution of the thesis addresses the relationship between relatedness and regional development. So far, most of the empirical analysis in the literature is on the relationship between relatedness and diversification at the regional level. While Chapter 6 exactly contributes to this body of literature by demonstrating that regions move through an occupation space by diversifying into occupational specialisations related to the existing set of the region, the chapters 3 and 5 enhance the understanding of how related variety affects different regional outcomes such as employment growth and regional innovativeness. Chapter 3 analyses the effects of related variety on regional employment growth in Germany both from a traditional industry perspective as well as a novel industrial-functional perspective. Chapter 5 approaches the role of relatedness in R&D efforts and its effects on regional innovation. The chapter argues that the effects of R&D subsidies go beyond the extension of organisations' monetary resources invested into R&D and tests if supporting R&D collaboration generally facilitates regions' innovation growth, or whether the degree of relatedness in R&D is of crucial relevance in this case.

1.5 Outline of the thesis

The thesis consists of five separate chapters all dealing with the relationship between related variety and economic development in Germany. They are sorted in the chronological order in which they were written. The following paragraphs present a short outline of the main research questions and how these are addressed in each chapter.

Chapter 2

The chapter adopts a relatedness perspective on regional industrial clusters structures based upon inter-industry input-output linkages. Ever since Porters (1990) seminal work, there has been a debate on how to identify industrial clusters in an appropriate and systematic way (Martin and Sunley 2003). Most empirical approaches focus on measures of concentration of one industrial sector. The analysis of vertically related variety – defined herein as industrial clusters' structures connected by dominant inter-industry linkages – in this context is a field of growing interest (Cainelli et al. 2015). The perspective on *inter-industry input-output linkages* is of importance because the spatial proximity of interlinked industry activities is found to be a major source of industrial co-agglomeration (Ellison et al. 2010), as well as a driver of performance of industrial clusters both in the short- and long-term (Maskell 2001, Kubis et al. 2012). In chapter 2 we raise the following research question:

Research question chapter 2:

To what extent are industrial cluster structures in Germany characterised by vertically related variety?

To answer this question, we adopt a method developed in input-output analysis (Schnabl 1994). This method is the entropy-based qualitative input–output analysis (QIOA). Using information from national input-output tables from Germany, the QIOA transforms quantitative information about the relative as well as the absolute importance of inter-industry flows into qualitative information. This selection of relevant flows is required to create insights into the core structures and the direction of intermediate purchases and sales relations within industrial clusters at the regional level in Germany. The regionalisation of the national industry templates is carried out with the allocation of branch-specific production values on regional employment. As a result, the paper shows concentrations of vertically related industrial clusters in only 27 of 439 German districts. The spatial allocation shows clusters with vertically related variety in the large urban areas such as Munich, Berlin, Hamburg, Cologne, and Frankfurt, while the south-west of Germany (Baden-Wuerttemberg) and the Ruhr area display many spatially proximate vertically related industrial clusters. In contrast, East Germany falls short in this context.

Chapter 3:

In chapter 3, we address the role of related variety on regional employment growth. As stated above, the concept of related variety questions the hypothesis that industrial diversity *per se* generates knowledge spillovers. It is argued that “knowledge will spill over effectively only when complementarities exist among sectors in terms of shared competences” (Boschma and Iammarino 2009, p. 290). In a first step, we transfer the conventional approach to identifying the effects of related variety, as developed in Frenken et al. (2007), to the case of Germany. We present estimates on the effects of related variety on regional employment growth at the level of labour market regions in the period 2003 to 2008.

Frenken et al. (2007) apply an entropy grounded measure of related variety that relies on the classification of economic activities in the standard industrial classification scheme (SIC). In a second step, we argue that sole reliance of the concept of related and unrelated variety on the SIC classifications remains debatable. We argue that conceptual progress can be made when the focus of analysis goes beyond solely considering industries and develop an industry-functional based approach that distinguishes degrees of industrial relatedness in the occupational-functional groups of *White Collar*, *Blue Collar* and *R&D* workers. Consequently, we put forward the following research questions:

Research questions chapter 3:

Does related variety spur regional employment growth in Germany? Do the effects of related variety vary by categories of occupational functions?

We answer these questions by using the information on the universe of employees working in German manufacturing industries. Empirical estimations follow a spatial panel approach (Elhorst 2003, 2010) that takes into account a spatial lag of the dependent variable and spatial autoregressive disturbances. The regression results support the need for a more differentiated view on (un-)related variety in the discussion on regional employment growth. They highlight the importance of controlling for regional functions in the production process. The results indicate that the positive effect of related variety is driven by high degrees of relatedness in the regional *R&D* and *White Collar* functions. Contrary, the effects of unrelated variety are spurred by *Blue Collar* functions in this period.

Chapter 4:

Chapter 4 discusses the concept of related variety from a perspective of a distinctive economic function that is organisational R&D. The technological complexity of modern products and services increases the difficulty for organisations to hold all resources needed to sustain their competitive advantages (Harrison et al. 2001). While this contributes to a more widespread use of interactive knowledge generation to enhance organisations' performance (Dyer and Singh 1998), it also opens up the question of who is the right partner for R&D collaborations over time. The chapter addresses the question of 'right' industrial partnering and argues that firm-level information on R&D projects can be used as an alternative source for measuring technological relatedness of industries that goes beyond the predominantly applied information on patent classes or patent citation.

We further develop an argument that the concept of related variety can benefit from a differentiation into the dimensions of similarity and complementarity (Makri et al. 2010). These two dimensions of relatedness are intended to shape the quality and quantity of collaboration outcomes of economic agents via underlying differences in R&D strategies such as exploitation (similarity) and exploration (complementarity). Complementarity is defined empirically by the co-occurrence of two industries in a joint R&D collaboration project. Based on the argument that organisations' resources must fit for enabling collective learning and innovation, we use this co-occurrence of firms in collaborative R&D projects to assess the inter-sectoral technological complementarity between 129 sectors in Germany. The results are mapped as complementarity space for the Germany economy showing each industry pair's potential for complementary resource partnering. The chapter puts forward the following research questions:

Research questions chapter 4:

What is the structure of inter-sectoral resource complementarity in the German economy? Does this structure change over time? Is the complementarity space able to reflect the rise of certain key technologies such as ICT?

We address these questions by using a novel dataset for Germany that includes comprehensive information on federally subsidised R&D projects. The complementarity space and its dynamics from 1990 to 2011 are analysed by means of social network analysis. The measures applied comprise of a sector's degree and betweenness centrality (Wasserman and Faust 1994). To identify patterns of clustering, fragmentation and rich-clubs in the complementarity space, the chapter relies on the measures of global clustering (Opsahl et al. 2008). The results illustrate sectors being complements both from a dyadic and network perspective. This latter is important, as complementarities may only become fully effective when integrated into a complete set of different knowledge resources from multiple sectors. The dynamic perspective, moreover, reveals the shifting demand for knowledge resources among sectors in different time periods as exemplified by the ICT sector.

Chapter 5:

In contrast to chapter 4, chapter 5 addresses the similarity dimension of the relatedness. Again we make use of the dataset for Germany that includes information on federally subsidised

R&D projects. By using the co-occurrence of two industries in a specific technology class while focussing on single R&D projects only, the chapter argues that this allows tracing the similarity dimension of relatedness (Makri et al. 2010). This means that technological similarity is defined as given when firms from different industries contribute independently of each other to progress within a similar narrow technological domain. This should allow creating benefits from their mutual absorptive capacity with positive effects on innovation quantity. Consequently, the chapter relates the measure of partner resource similarity in subsidised R&D projects to the regions' industry-specific innovation growth rates. The following research question is addressed:

Research question chapter 5:

Does the degree of similarity of partner resources in subsidised R&D projects contribute to increases in regional innovation outputs?

We answer this question by employing a two-stage Heckit approach. After rescaling innovation growth rates and cleaning them from heteroscedasticity, this should address potential endogeneity issues related to the allocation of public R&D funds (Czarnitzki et al. 2007). The second stage estimation applies a spatial simultaneous autoregressive error model that addresses both spillovers through space as well as dependencies potentially arising from relational spillovers (Maggioni et al. 2007). The empirical results substantiate the claim that regions can benefit from collaborative R&D subsidies when providing access to partners from industries characterised by similar resources and when embedding regions into central positions in cross-regional knowledge networks.

Chapter 6:

Chapter 6 addresses the role of relatedness in the regional human capital structures (Boschma et al. 2009). Recent literature shows that regional skill accumulation is driven by the interplay of people holding different skill-intensive occupations (Florida et al. 2008). Hence, this chapter contributes to the understanding of why and how skills accumulate in regions by adopting a relatedness perspective based upon patterns of occupational co-specialisation in regions. The occupational composition of a region is supposed to matter for dynamic regional skill accumulation via its effect on the entry (exit) of related (unrelated) occupational specialisation. That is, the current occupational composition places a region in a so-called occupation space that determines future regional occupational diversification possibilities. The chapter addresses the following research questions:

Research questions chapter 6:

Does occupational relatedness have similar implications for regional occupational diversification than other relatedness patterns? Does occupational relatedness contribute to regional human capital accumulation?

These questions are answered by using information about the spatial distribution of the universe of employees subject to social security contributions in the German manufacturing sector in the period 1992 to 2010. For the calculation of occupational relatedness, the chapter follows Muneepeerakul et al. (2013) and uses the co-occurrence of two occupational specialisations in a region as a measure of occupational relatedness. The chapter finds that the probability of entry into new occupational specialisations in a region increases if the level of relatedness around this occupation increases. This effect is even more pronounced when considering human capital intensive occupations. In addition to that, as expected, we find that the relationship between relatedness and exits from occupational specialisations is negative.

1.6 Overview of publication status and co-authorships

The chapters are a result of collaborative work on this topic with colleagues from across Germany. Some chapters are already published in scientific journals.

Chapter 2 on "The Identification of Regional Industrial Clusters Using Qualitative Input-Output Analysis (QIOA)" has been published in Regional Studies (Volume 45 (1), 2011, p. 89-102) and is co-authored with Mirko Titze and Alexander Kubis, both colleagues at the Halle Institute for Economic Research (IWH) at the time the paper was written.

Chapter 3 on "Related Variety, Unrelated Variety and Regional Functions: A spatial panel approach" has been published in the working paper series Papers in Evolutionary Economic Geography at Utrecht University in 2013 and is currently under review in a journal. The paper is also co-authored with Mirko Titze and Alexander Kubis.

Chapter 4 is a joint work with Tom Broekel from the University of Hannover. The respective paper titled "The Structure and Evolution of Inter-sectoral Technological Complementarity in R&D in Germany from 1990 to 2011" has been published in the Journal of Evolutionary Economics (Volume 25 (4), 2015, p. 755-785).

Chapter 5 is the outcome of the collaboration with Tom Broekel from University of Hanover and Matthias Duschl as well as Thomas Brenner from the University of Marburg. The paper on "Joint R&D Subsidies, Related Variety, and Regional Innovation" is forthcoming in the International Regional Science Review.

Chapter 6 is entitled "The rise and fall of occupational specialisations in German regions from 1992 to 2010 – Relatedness as driving force of human capital dynamics" and represents a single authored paper which is currently under review in a journal.

Chapter 2

The identification of regional industrial clusters using qualitative input–output analysis

2.1 Introduction

This paper explores the potential arising through the application of qualitative input–output analysis (QIOA) to identify regional industrial clusters. It follows a method developed by Schnabl (1994), who uses national input–output tables to discover important qualitative inter-industry linkages. We enhance this method by introducing a framework to regionalise the identified national industry templates and create insights into the spatial allocation of potential vertical industrial clusters in Germany's NUTS-3 regions. To our knowledge, this method has not yet been applied to the subject of industrial clusters. Thus the paper reveals that the method contributes usefully to the identification of potential buyer–supplier linkages within regional industry activities as a starting point for regional planning policy.

Regarding structure, the paper is divided into five parts. After the introduction, the second part reviews the literature concerned with inter-industry linkages and spatial proximity within the cluster concept. The third section describes alternative methods of using nationwide input–output tables for industry cluster analysis. The fourth part describes the technique of qualitative input–output analysis, the selection-criterion for concentrated economic sectors and the regionalisation to NUTS-3 level with the help of employment data. The fifth part presents the results obtained from German regions, and develops a classification scheme that characterises different forms of identified vertical industry clusters. The paper ends with an assessment of how these results can be transferred to regional planning policy, and presents further research questions that emerge with the use of this method.

2.2 The cluster concept

It is a basic observation that economic activity is concentrated in space and, following this, there is increasing attention being paid to the forces of agglomeration and the role of location in economic development. Theoretical foundations of the analysis of local industry concentrations are given by the concept of agglomeration economies (Marshall 1920) and external localisation economies (Hoover 1948). Porter (1990) picked up these ideas in the explanation of the competitiveness of national economies and later applied them to concentrations of economic activity in space. He introduced the influential cluster concept to explain industry concentration which has now become a standard concept in the economic localisation field (Martin and Sunley 2003).

Porter (1998) defines clusters as 'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities'. This definition is ambiguous, as it is vague in terms of geographical scale and internal socio-economic dynamics, leading to a diversity of further definitions and empirical applications (Martin and Sunley 2003). Following this, there is still a lack of consent as to what defines a cluster. As well as a minimal agreement about the need of spatial proximity, the need for linked industries can be acknowledged in the literature. This study draws mainly on these two criteria for the identification of industrial clusters.

The issue of spatial proximity has thereby been of rapidly increasing importance in the cluster literature since Czamanski and Ablas (1979) made a distinction between industrial complexes and industrial clusters regarding the spatial co-agglomeration of these industry groups. Spatial proximity of interlinked industry activities is regarded as influencing the performance of these sectors, and regional clusters in both the short and long term (Maskell 2001). While the short-term focus points out the temporal and qualitative availability of key inputs and services (Feser and Bergman 2000), the long-term perspective stresses the necessity of interaction with other regional agents (buyers, suppliers, institutions) as sources of competitive advantages through innovation, knowledge spillovers and interactive learning (Lucas 1988, Feldman 1999). Temporal and qualitative availability of inputs from specialised suppliers is of increasing importance as industries are restructuring their relationships with members of the value chain, focusing on core competencies and permitting greater co-ordination in design and production (Feser and Bergman 2000). Larsson (2002) and Frigant and Lung (2002) highlight that new production concepts such as Just-in-Time (JIT) or modular production focus on reliability so much that temporal and spatial proximity becomes of strategic importance. While these studies focused on the vehicle industry, Cannon and Homburg (2001) use a wider sample of firms, and stress the pecuniary advantages arising from the geographical closeness of suppliers' facilities to customers' buying locations, thus lowering the customer firms' costs.

Additionally, long-run empirical studies tend to emphasise that agents that are concentrated spatially benefit from knowledge externalities (Marshall 1920). These knowledge spillovers appear to be spatially bounded (Jaffe et al. 1993, Audretsch and Feldman 1996), as closer proximity allows more frequent face-to-face contact, facilitating the exchange of knowledge and fostering transfer skills and innovation (Knoben and Oerlemans 2006). Oerlemans and Meeus (2005) indicate that these interactions along the value chain could be even more important, since business agents (buyers and suppliers) embody the most valuable product-related technical knowledge and therefore affect the innovative and economic performance of the firm. This might be necessary not only for tacit knowledge but also for codified knowledge, as the assimilation of both still require tacit knowledge, and thus spatial proximity (Howells 2002, Boschma 2005). The effect of spatial proximity alone has been challenged in the recent literature on innovation, inter-firm collaboration and firm performance. Torre and Rallet (2005) stress the fact spatial proximity on its own cannot create interaction or collaboration, and that other forms of proximity (organised proximity, temporal spatial proximity, for example) could have increasing importance for successful interaction. Spatial proximity may act in a complementary way in building and increasing institutional, social, organisational or cognitive proximity (Boschma 2005).

To capture these different forms of proximity, we choose to focus on inter-industry flows, as intermediate flows of goods are indicators of inter-firm interactions encouraging company performance. To overcome the problems of the empirical operationalisation of Porter's cluster concept the paper defines clusters from a more functional perspective as 'networks of producers of strongly interdependent firms (including specialised suppliers) linked to each other in a value adding production chain' (Roelandt and Den Hertog 1999). Using this form of definition we are able to integrate the cluster concept in an input-output framework allowing using methods of input-output analysis. Furthermore, we search for spatial concentrations (the necessity for a critical mass, according to Steinle and Schiele 2002, Walcott 2002) of these benchmark value chains (Feser 2005) at the regional level to fulfil the requirements of spatial proximity and interaction along the value chain.

2.3 The analysis of regional industry interactions in clusters

For the generation of information about vertical industry linkages it is necessary to use input–output tables. The literature offers several approaches to solve this problem. The basic commonality is the division of inter-industry linkages into important and unimportant flows of goods. Recent literature focuses mainly on four concepts. An elementary cluster analysis is proposed by Bijnen (1973). He focuses only on the strongest inter-industry linkages as main points of interest, while neglecting possibly weaker but also important linkages (see also Bellet et al. 1989 – 'Direct Flow Analysis', Peeters et al. 2001 – 'Method of the Maxima'). Feser and Bergman (2000) use principal components factor analysis where measures of direct and indirect linkages calculated from inter-industry trade information were treated as variables to measure the relative strength of a given industry and a derived factor. As this approach is not based on the absolute or even the relative size of transactions between the sectors, they use the similarity of intermediate purchases and sales structure to group different industries into one cluster (Oosterhaven et al. 2001). Thus highest-loading industries were treated as members of an industrial cluster (see also Vom Hofe and Dev Bhatta 2007 and Kelton et al. 2008 for recent applications).

Oosterhaven et al. (2001) use intra-regional intermediate sales matrices. They introduce three criteria to determine which direct linkages are important for potential cluster building. First, absolute intermediate transaction size should be larger than the average intermediate transactions size. Further, the relative importance of intermediate transactions is covered through an above-average intermediate input coefficient and an above-average intermediate output coefficient, thus stressing the importance of intermediate purchases and sales. Oosterhaven et al. (2001) point out that the absolute size is the most important criterion, as it looks directly at the strength of the linkages, but they do not take absolute and relative indirect effects into account, which seems to be of increasing importance as the absolute size of intermediate transactions is increasing.

Another method to measure inter-industry linkages is presented by Dietzenbacher (1992); for a recent application, see Midmore et al. (2006), who use an eigenvector method associated with a dominant eigenvalue of the direct coefficients matrix in a search for key industrial sectors. The focus of this method lies in the ranking of regional industries in terms of forward and backward linkage potential with the help of industry weights that filter out the effects of different primary input intensities in supplying industries (Midmore et al. 2006). Another contribution that has not yet been applied to the cluster concept was developed by Schnabl (1994). This method of qualitative input–output analysis is now discussed in further detail.

2.3.1 Methodology

The basic principle of qualitative input–output analysis is the differentiation of important and unimportant intermediate flows of goods within the national input–output framework. For practical purposes, we shall only take into account those inputs that exceed a developed endogenous filter rate. This method transforms quantitative information about the relative or absolute importance of these inter-industry transactions into qualitative information. On the one hand, this contributes to a loss of information; but on the other, it leads to the selection of required relevant input flows and creates insights into the core structures of intermediate purchases and sales relations. Mathematically, we carry out a binary transformation of input flows between two industries, *i* and *j*. An input flow s_{ij} becomes 1 if it exceeds a filter rate *F*, and 0 otherwise. This transforms the basic input–output table into the so-called adjacency matrix *W*:

$$(2.1) \qquad w_{ij} = \begin{cases} 1, \text{if } s_{ij} > F \\ 0, \text{otherwise} \end{cases}$$

In this paper, we are interested primarily in inter-industry linkages. For our purposes, the examination of intra-industry linkages ($i = j$) is of secondary importance. Thus the elements of the main diagonal are fixed at 0. The fundamental question arising is: what is the optimum threshold value determining the value of the filter rate *F*? This includes the question of which input flows are relevant. In our paper we use minimal flow analysis (MFA) to detect the optimal filter rate F_{opt}. This method was substantially developed by Schnabl (1994). The optimal filter rate will be calculated using an iterative process. The initial point is the layer-wise separation of the input–output information. Basically, relation (2.2) is essential, where *x* is the vector of production values, *C* stands for the Leontief inverse matrix, and *y* equals the vector of total demand. Further the Leontief inverse can be written as Eulerian series, in which *I* is the unit matrix and *A* is the matrix of input coefficients.

$$(2.2) \qquad x = C \cdot y = \left(I + A + A^2 + A^3 \ldots\right) y$$

The real total demand vector *y* can be replaced by a synthetic vector. This shows the potential of this method. With the application of the real final demand vectors, absolute values of intermediate good flows can constitute the major research interest, while, using synthetic vectors, the relative importance of inter-industry transactions determines the relevant threshold value and input flows. In this paper we have chosen to use a synthetic vector, because the calculated structure reflects the technical relations and relative importance of the sector. After diagonalization, this vector corresponds to the unit matrix *I*. The real total demand vector would distort the desired technical structure (Schnabl 1994).

The next step is to develop a set of transaction matrices, based on the decomposition of the Leontief inverse with the help of Eulerian series. We find the transaction matrix *T*, where the matrix of input coefficients is multiplied by the diagonal matrix $\langle x \rangle$ of the vector of production values *x*.

$$(2.3) \qquad T = A \cdot \langle x \rangle$$

According to relation (2.2), we can separate (2.3) into the following layers:

$$(2.4)\quad \begin{aligned} T_0 &= A \cdot \langle y \rangle \\ T_1 &= A \cdot \langle A \cdot y \rangle \\ T_2 &= A \cdot \langle A^2 \cdot y \rangle \\ T_3 &= A \cdot \langle A^3 \cdot y \rangle \quad etc. \end{aligned}$$

The exponentiation of the matrix of input coefficients continues until no elements t_{ij}^k of matrix T_k exceed a given filter level F. This transformation leads to binary layer specific adjacency matrices W_k, with

$$(2.5)\quad w_{ij}^k = \begin{cases} 1, \text{if } t_{ij}^k > F \\ 0, \text{otherwise} \end{cases} .$$

Using equation (2.6), it is possible to reproduce the quantitative layer-wise information included in the Leontief inverse into qualitative information in the adjacency matrix.

$$(2.6)\quad W^k = \begin{cases} W_k \cdot W^{k-1}, \text{if } k > 0 \\ I, \text{if } k = 0 \end{cases}$$

W^k represents the connection between layer-wise varying adjacency matrices W_k, while including the increasing irrelevance of the flow of intermediate goods between the sectors i and j at higher levels of k.

In the next step, we calculate the so-called dependence matrix D by adding the product matrices W^k layer-wise. We use Boolean addition (marked by #) as it is important to know whether a direct or indirect connection exists, but not how many steps are needed to fulfil the filter criterion.

$$(2.7)\quad D \; = \# \left(W^1 + W^2 + W^3 + \ldots \right)$$

Finally, we derive the connectivity matrix H.

$$(2.8)\quad H = D + D' + D$$

Equation 2.8 now generates information about the kind of relation between two sectors. Elements of D take only values of 0 or 1, therefore the set of elements h_{ij} in the connectivity matrix H is restricted to values between 0 and 3. The meaning of these elements can be interpreted as follows:

- 0, no link between sector i and j exists, i and j are isolated;
- 1, a weak relation between the sectors i and j is identified; for example, to reach sector j (starting from i) we 'travel' in the wrong direction;
- 2, a uni-directional relation exists between sector i and j, meaning i supplies j; and
- 3, we can denote a bilateral relation between the two sectors, which means that sector i supplies j and i receives from j.

For the purpose of this paper, the uni-directional and the bilateral relations are important. Regarding equation 2.5 we see that the value of the filter rate *F* determines both kinds of relations. We are coming back to the question: what is the right filter rate *F*? Using the Minimal Flow Analysis Schnabl (1994) suggests to apply the information measure according to Shannon and Weaver (1949) and second, the average value of the elements of the so-called resulting connectivity matrix H_{res}. Following Shannon and Weaver (1949) we calculate the optimal filter rate *F* by maximising the information content of the connectivity matrix *H*. To measure the information content they used the entropy *E*. Entropy measures offer important insights in the variety in distributions at particular moments in time (Frenken 2007). Applied to input-output tables the entropy index refers to the degree of randomness in the choice of input coefficients as reflected by the skewness of a distribution. A skewed distribution reflects a situation in which input coefficients hardly differ, while a flat distribution reflects a situation in which input coefficients vary significantly (Frenken and Nuvolari 2004).[1] If input coefficients are grouped with the help of threshold values, entropy can be used as a suitable indicator to determine to what extent important inter-industry linkages have emerged (Schnabl 2000). *E* is maximised when the probability of occurrence is equal for each element (in our case: 0, 1, 2 and 3). Starting with a low filter rate we can denote a high share of uni-directional (h_{ij} = 2) and bilateral relations (h_{ij} = 3). With increases in the filter rate, the bilateral relations become uni-directional or weak relations (h_{ij} = 1). At the highest filter level, all relations are isolated (h_{ij} = 0). To determine *E* we first calculate the final filter rate F_f. This breaks off the last bilateral linkage (h_{ij} = 3). Second, we apportion the filter into 50 equidistant filter steps *l*. Third, we calculate the entropy E_l for each of the 50 filter steps, using equation 2.10. The variable *p* indicates the probability for an element h_{ij}, *n* is determined by the co-domain of h_{ij}, and $\log_2$ notes the logarithm dualis.

(2.9) $E_l = \sum_n \left(p_{l\,n} \cdot \log_2 \left(1 \middle/ p_{l\,n} \right) \right)$, notification:

The optimum filter step l represents the maximal entropy E.

(2.10) $\max E_l \;\forall\; l = 1,...,50$

Maximising entropy usually produces clear results but flat distributions sometimes lead to difficulties to assign the maximum to a filter value. Therefore Schnabl (1994) recommended using a second method to decide on the optimal filter rate to get a robust measure for the endogenous threshold. In this paper we use the average value of the elements $h_{ij_{res}}$ of the resulting connectivity matrix H_{res}. This matrix is calculated as follows:

(2.11) $H_{res} = \left(\sum_{k=1}^{50} H_l \right) - 100$

[1] Albeit Frenken and Nuvolari (2004) used entropy statistics to determine the evolution of technological variety and dominant designs, this application can be transferred to the identification of dominant inter-industry linkages in the same way. Further applications of entropy statistics can be found for example in the analysis of regional industrial diversification, industrial concentration or income inequality (Frenken 2007).

H_{res} indicates the hierarchy within the identified structure of inter-industry linkages and therefore gives a special focus on strong uni-directional and bilateral connections aiming to achieve the goal of a reasonable reduction of inter-industry linkages. The optimal filter step l_{opt} is derived from the sum of elements $h_{ij_{res}}$ greater than 0, divided by the number of elements greater than 0. We finally apply the average of the two measured filter steps as the optimal filter rate.

2.3.2 The identification of spatial concentrations of industrial sectors

Identifying vertical industry linkages is the first step in industry cluster analysis. In this section, we present the concept used to identify a spatial proximate critical mass of relevant industries (Steinle and Schiele 2002, Walcott 2002). Therefore, we have to transfer the information about intermediate inputs to geographic units. We apportion the intermediate input of a certain industrial sector (*input*$_i$) to Germany's NUTS 3-regions according to the regional share of employment in the relevant sector (employment x_{ir} in sector i and region r divided by the total employment in this sector x_i).[2] As a result, we receive the intermediate input of a certain industrial sector, which is obtained from a region (*input*$_{ir}$).

$$(2.12) \quad input_{ir} = \frac{x_{ir}}{x_i} \cdot input_i$$

With the help of concentration indices we can identify industrial sectors and regions that are characterised by a concentrated delivery of intermediate inputs. To calculate, we draw on the Gini coefficient, the Herfindahl index and the concentration rate. Although alternative measures of concentrations (Ellison and Glaeser 1997, Duranton and Overman 2005) have been used in recent literature, we consider these concentrations measures to be reasonable for a first approximation of different forms of identified clusters. This includes, for example, clusters in the form of hub and spokes, where the spatial concentration of inputs is created by small numbers of major firms realising internal economies of scale but being important for spatial proximate concentrate suppliers (Markusen 1996). The Gini coefficient considers the total number of regions N, the rank of the region r, and the share s of intermediate inputs that are delivered from the region in a certain industrial sector (according to Suedekum 2006).

$$(2.13) \quad Gini_i = \frac{N}{N-1} \cdot \left[\frac{2}{N} \cdot \frac{\sum_{r=1}^{N} (r \cdot s_{ir})}{\sum_{r=1}^{N} s_{ir}} - \frac{N+1}{N} \right] \text{ with } s_{ir} = \frac{input_{ir}}{input_i}$$

Another concentration measure that is principally used in the literature is the Herfindahl index *H*. This results from the sum of squares of regional intermediate input deliveries divided by the square of the total intermediate input deliveries in a certain industrial sector *i*.

[2] This paper uses the concentration rate, Gini coefficient and the Herfindahl index. Other concentration measures do not bias substantially, as Herfindahl-Hirshman index (HHI) of the plant size distribution as part of the Ellison-Glaeser index or the concentration index of Maurel and Sedillot (1999) is very small for all industries in Germany (Suedekum 2006). For the identification of industrial clusters with the help of Ellison-Glaeser index see Alecke et al. (2008).

$$(2.14)\quad H_i = \frac{\sum_{r=1}^{N} input_{ir}^2}{input_i^2} \text{ with } input_i = \sum_{r=1}^{N} input_{ir}$$

The two concepts of measurement discussed here describe whether a certain industrial sector is concentrated or not. However, we do not receive information about regions belonging to the important production locations in Germany. For this purpose, the concept of concentration rate is suitable. In this paper, a certain industrial sector belongs to set of concentrated industrial sectors when a maximum of twenty-five regions account for 50 per cent of total intermediate input deliveries. Furthermore, these twenty-five regions are regarded as being important production locations in Germany.

$$(2.15)\quad i \in M\{\text{concentrated industrial sectors}\}\text{if}\left(\sum_{\text{r}=1}^{25} input_{ir}\right) > 0.5 \cdot input_i$$

To transfer the identified industrial structure and concentration rates to the regional level, we deal repeatedly with equations 2.6 and 2.15. Applying the derived optimum filter rate, the first adjacency matrix w_{ij}^1 offers insights into the relevant direct inter-industry linkages, while *D* gives a summary of relevant direct and indirect relations. For this purpose, regional cluster structures are derived by equation 2.16, focusing on spatial proximate direct inter-industry linkages.

$$(2.16)\quad w_{ijr}^1 = \begin{cases} 1, \text{if } t_{ij}^1 > F_{opt} \\ 0, \text{otherwise} \end{cases} \left| \begin{array}{l} i, j \in M\{\text{concentrated industrial sectors}\} \\ \cap\, r \in M\{\text{important production locations}\} \end{array} \right.$$

The following example illustrates this concept. The left-hand side of Figure 2-1 shows a potential national industrial structure and the corresponding structural relations. In the (exemplary) region (to the right in Figure 2-1) only sectors 2 and 3 are concentrated. For this reason, the links from sector 1 to 2 and from 3 to m drop out. Thus the national industrial structure acts as a template for the regional economic structure, showing regional specialisations within different value chains.

National industrial structure

	1	2	3	…	m
1		1	0		0
2	0		1		0
3	0	1			1
…					0
m	0	0	0	0	

Regional structure (bold numbers = concentrated industrial sectors in that region)

	1	**2**	**3**	…	m
1		0	0		0
2	0		1		0
3	0	1			0
…					0
m	0	0	0	0	

Figure 2-1. The transfer of industrial structures and concentration rates to regions.

At this point we need to pay attention to how this structural graph can be interpreted. The regional structural graph does not show the real supply chains. We assume these industrial linkages to exist from a production engineering point of view, helping regional agents to understand potential inter-industry relations, which might benefit from spatial proximity, as indicated by cluster theory and empirical studies (particularly case studies). On the other hand, potentially missing parts of value chains can be identified at the regional level, with further implications for regional planning policies. We now want to turn to the application of the presented method for Germany's NUTS-3 regions.

2.4 Germany's regional vertical industry clusters

Data and assumptions

To analyse inter-industry linkages, we use data from the German Input–Output Table 2003 (Statistical Office of Germany 2008). This table includes seventy-one industrial sectors (CPA – Classification of Products by Activity). We excluded imports from the analysis as our aim is to detect regional production linkages. We calculate the concentration of industrial sectors (NACE code) using the data for the year 2003 from the German Federal Employment Office at the NUTS-3-level (districts, district-free cities). Our analysis is based on three fundamental assumptions. First, we assume that the CPA classification is nearly equivalent to the NACE code. The second assumption concerns the (technical) production structure in the NUTS-3 regions. We suppose that the national industry templates are applicable to the regional level, meaning that fundamental relations between different economic sectors are identical. Following this, the production process of an automobile in terms of input coefficients in Stuttgart is identical to that in Bremen or Zwickau. Third, we suppose that productivity is exactly equal in all German NUTS-3 regions in a certain industrial sector, allowing us to portion the intermediate inputs to the NUTS-3 regions according to its regional share of employment in the relevant industrial sector.

Regional inter-industry linkages

According to the method mentioned above, we first need to identify the optimum filter rate for the German input–output in 2003. The results presented in Table 2-1 show entropy E for the 50 equidistant filter steps. For reasons of simplification, irrelevant filter steps have been taken out of the description.

Filter step	Filter	Entropy	Number of different inter-industry linkages				Sum of overall connections possible
			Isolated	Weak uni-directional	Uni-directional	Bilateral	
1	0.0001	84.33	418	174	174	4,204	4,970
2	0.0016	144.95	486	590	590	3,304	4,970
3	0.0032	171.47	602	839	839	2,690	4,970
4	0.0048	194.38	848	1,152	1,152	1,818	4,970
5	0.0064	199.49	1,066	1,289	1,289	1,326	4,970
6	0.0081	197.15	1,476	1,325	1,325	844	4,970
7	0.0097	194.09	1,692	1,279	1,279	720	4,970
8	0.0113	186.84	1,962	1,248	1,248	512	4,970
9	0.0129	175.96	2,344	1,131	1,131	364	4,970
10	0.0145	169.27	2,512	1,087	1,087	284	4,970
...	...	...	...	...	...	...	...
49	0.0774	26,37	4,790	89	89	2	4,970
50	0.0790	-	4,796	87	87	0	4,970

Table 2-1. Filter steps and entropy. Source: Data use from Statistical Office of Germany, 2008 (Fachserie 18 Reihe 2, Published 20.04.2007, Revised 07.05.2008); Authors' own calculation.

Entropy level is maximised at filter step 5, but according to Schnabl (1994) it is reasonable to use a second criterion for the identification of the optimum filter rate. The average value of the resulting connectivity matrix H_{res} indicates filter step 9 as optimum. The average of these two values leads us to filter step 7 as the optimum filter, with the value 0.0097. With the help of this filter we calculate the first layer adjacency matrix containing 521 inter-industry relations. Differences among the values in the Table 2-1 are caused by indirect effects between sectors, leading to more inter-industry linkages.

Regional concentrated economic sectors

In the next step we identify regionally concentrated economic sectors with the help of different concentration measures (see Table 2-2).[3] Out of the original seventy-one industrial sectors, a set of twenty-seven regional concentrated sectors could be identified.

Code[a]	Description	Gini	Number of districts
5	Fishing, fish farming and related service activities	0.84	15
10	Mining of coal and lignite, extraction of peat	0.96	6
11	Extraction of crude petroleum and natural gas	0.98	3
16	Manufacture of tobacco products	0.98	3
19	Manufacture of leather and leather products	0.84	16
21.1	Manufacture of pulp, paper and paperboard	0.82	23
22.1	Publishing	0.76	20
23	Manufacture of coke, refined petroleum products and nuclear fuel	0.96	4
24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	0.87	14
24	Manufacture of chemicals and chemical products	0.77	22
25.1	Manufacture of rubber products	0.85	14
26.1	Manufacture of glass and glass products	0.82	23
27.1–27.3	Manufacture of basic iron and steel and of ferro-alloys, tubes and other first processing of iron and steel	0.82	17
27.4	Manufacture of basic precious and non-ferrous metal	0.89	11
30	Manufacture of office machinery and computers	0.90	7
31	Manufacture of electrical machinery and apparatus	0.73	25
32	Manufacture of radio, television and communication equipment and apparatus	0.79	22
34	Manufacture of motor vehicles, trailers and semi-trailers	0.85	12
35	Manufacture of other transport equipment	0.86	13
40.2	Manufacture of gas, distribution of gaseous fuels through mains	0.85	13
60.1	Transport via railways	0.79	17
61	Water transport	0.92	5
62	Air transport	0.98	3
66	Insurance and pension funding	0.92	7
72	Computer and related service activities	0.78	18
73	Research and development services	0.85	13
92	Recreational, cultural and sporting activities	0.71	18

Table 2-2. Regionally concentrated economic sectors. Note: [a] German classification of economic activities, 2003 edition (see Federal Statistical Office of Germany, 2003 for details). Source: Data used from German Employment Agency, reference date: 30.06.2003; Authors' own calculation.

[3] This paper uses the concentration rate, Gini coefficient and the Herfindahl index. Other concentration measures do not bias substantially, as Herfindahl-Hirshman index (HHI) of the plant size distribution as part of the Ellison-Glaeser index or the concentration index of Maurel and Sedillot (1999) is very small for all industries in Germany (Suedekum 2006). For the identification of industrial clusters with the help of Ellison-Glaeser index see Alecke et al. (2008).

The exclusion of forty-four sectors leads to a reduction of relevant inter-industry linkages from 521 to 41. Subsequently, we assign this structure to the NUTS-3 level.

Subsumed results for Germany's NUTS-3 level show that, out of 439 regions, 257 (58.5 percent) do not have any concentrated economic activities according to our selection, while 182 accommodate at least one concentrated sector. To typify these concentrations we developed a characterisation scheme, which allows each region to be attached to a specified cluster type. According to our analysis two elements constitute industrial clusters, first the number of important production locations in the concerning region and, second the number of potential regional linkages. The specification of the two criteria allows us to build five classes. In class 1 no concentrated economic activity can be identified. Class 2 contains regions with only one important production location. Regions which were able to attract or generate more than one important production location can be divided into three classes. As the simple concentration of economic activity is no sufficient condition for the existence of vertical industrial linkages, regions without characteristics form class 3. Regions with multiple important production locations but only one vertical industrial linkage show first signs of vertical industrial clusters (class 4). Regions with multiple important production locations and multiple vertical linkages form class 5. To our understanding these regions are strong vertical industrial clusters. The classification scheme is presented in Table 2-3.

Number of linkages	Number of concentrated economic sectors 0	1	>1
No linkages	Class 1	Class 2	Class 3
1 linkage			Class 4
> 1 linkage			Class 5

Table 2-3. Characterisation scheme for concentrated economic activity. Source: Authors' own calculation.

Appling this classification scheme to the German NUTS-3 regions we were able to identify, first signs of horizontal clusters with a single concentrated economic sector in 110 regions. In 45 regions we could detect strong horizontal clusters in the sense of containing more than one non-related sector. Overall, only 27 regions (6.2 per cent) showed first signs of vertical clusters (16) or strong vertical clusters (11) according to the German input–output table, indicating that, at this spatial scale, only small number of regions are able to organise proximate production networks (compare Table 2-4).

Class	Description	Number of regions
1	Regions with no concentrated economic activity	257
2	Regions with signs of horizontal clusters	110
3	Regions with strong horizontal clusters	45
4	Regions with first signs of vertical clusters	16
5	Regions with strong vertical clusters	11

Table 2-4. Description of cluster classes. Source: Authors' own calculation.

Figure 2-2 shows the regional allocation of the five classes in Germany. Strong vertical clusters can be seen in the large urban areas of Munich, Berlin, Hamburg, Cologne and Frankfurt, while, in particular, the south-west of Germany (Baden-Wuerttemberg) and the Ruhr area display many spatial proximate concentrated economic sectors. Areas in the east of Germany fall short in this discussion. Only a couple of regions (Leipzig, Dresden, and Rostock as a maritime cluster) have successfully attracted concentrated economic activities, but most of the regions do not show any concentrations according to our classification scheme.

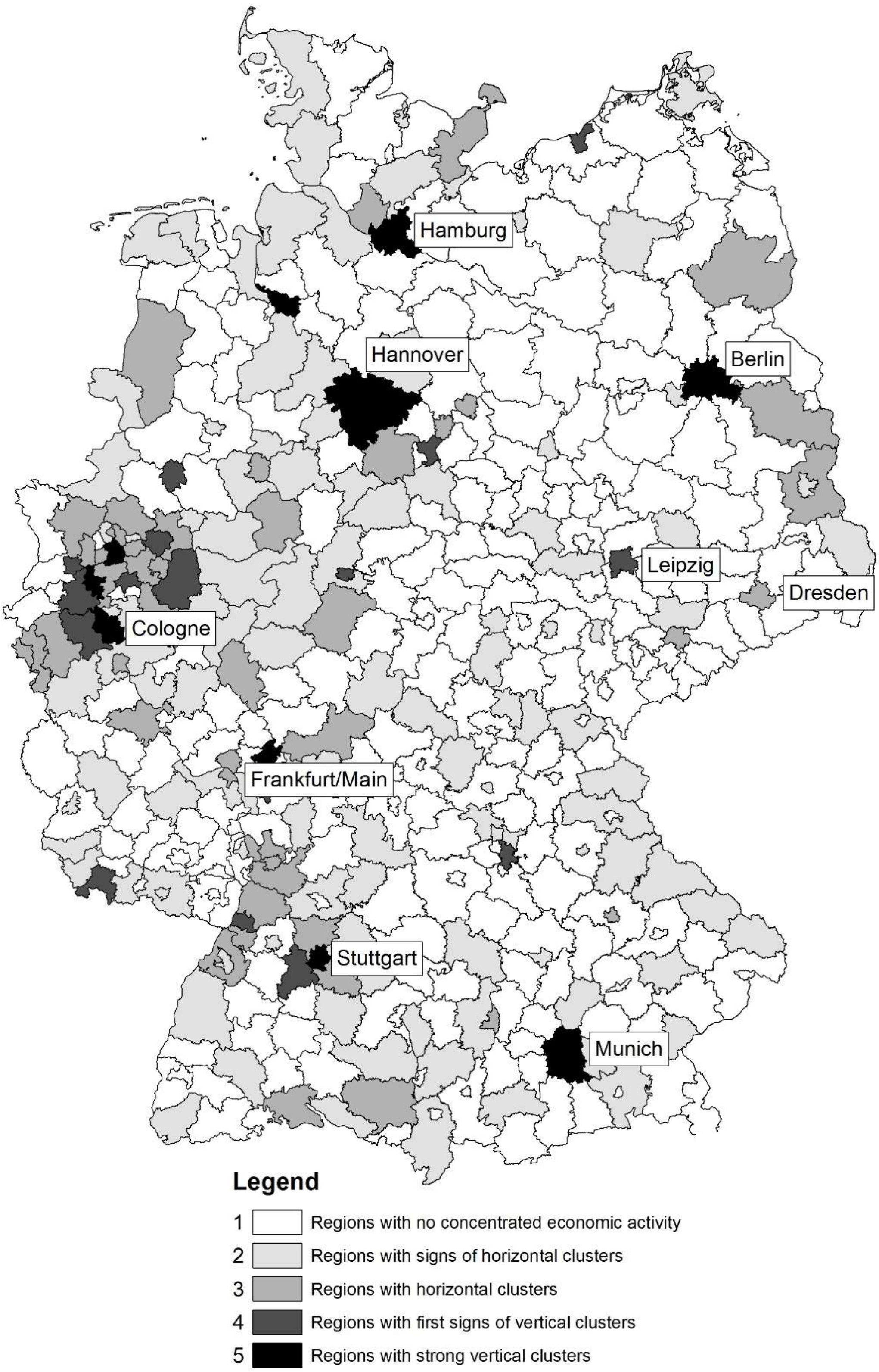
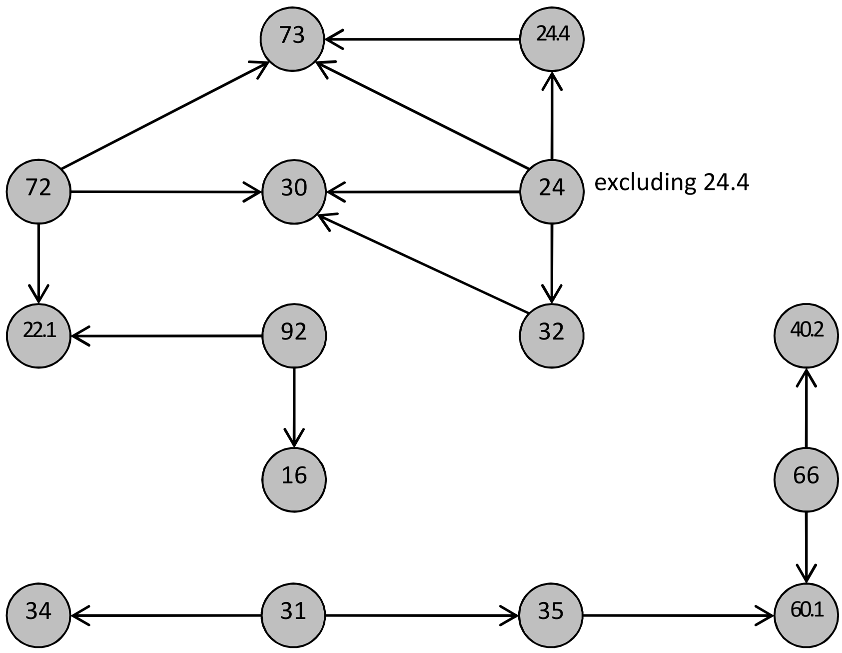


Figure 2-2. The spatial allocation of horizontal and vertical clusters at NUTS-3 level in Germany (2003). Source: Authors' own illustration.

As Martin and Sunley (2003) mentioned ‘clusters vary considerably in type, origins, structure, organisation, dynamics and development trajectories’. With the help of the approach presented, we are able to give insights in the specific characteristics of horizontal and vertical industrial clusters within an input-output framework, meaning that we can show different forms of the spatial organisation and structure of production networks. As an example, the results are presented in detail for the NUTS-3 region of Munich and the functional area of Stuttgart. Both regions have shown a positive economic development during the last 10 years.[4] Further their strong growth goes along with strong vertical clusters identified within the study.



Legend:

16	Manufacture of tobacco products
22.1	Publishing
24	Manufacture of chemicals and chemical products
24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus
32	Manufacture of radio, television and communication equipment and apparatus
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
40.2	Manufacture of gas, distribution of gaseous fuels through mains
60.1	Transport via railways
66	Insurance and pension funding
72	Computer and related service activities
73	Research and development services
92	Recreational, cultural and sporting activities

Figure 2-3. Structural graph for the NUTS-3 region of Munich. Source: Authors’ own illustration.

[4] Both regions have contributed to 15% of the overall growth of gross value added in Germany between 1996 and 2005 (author’s own calculation).

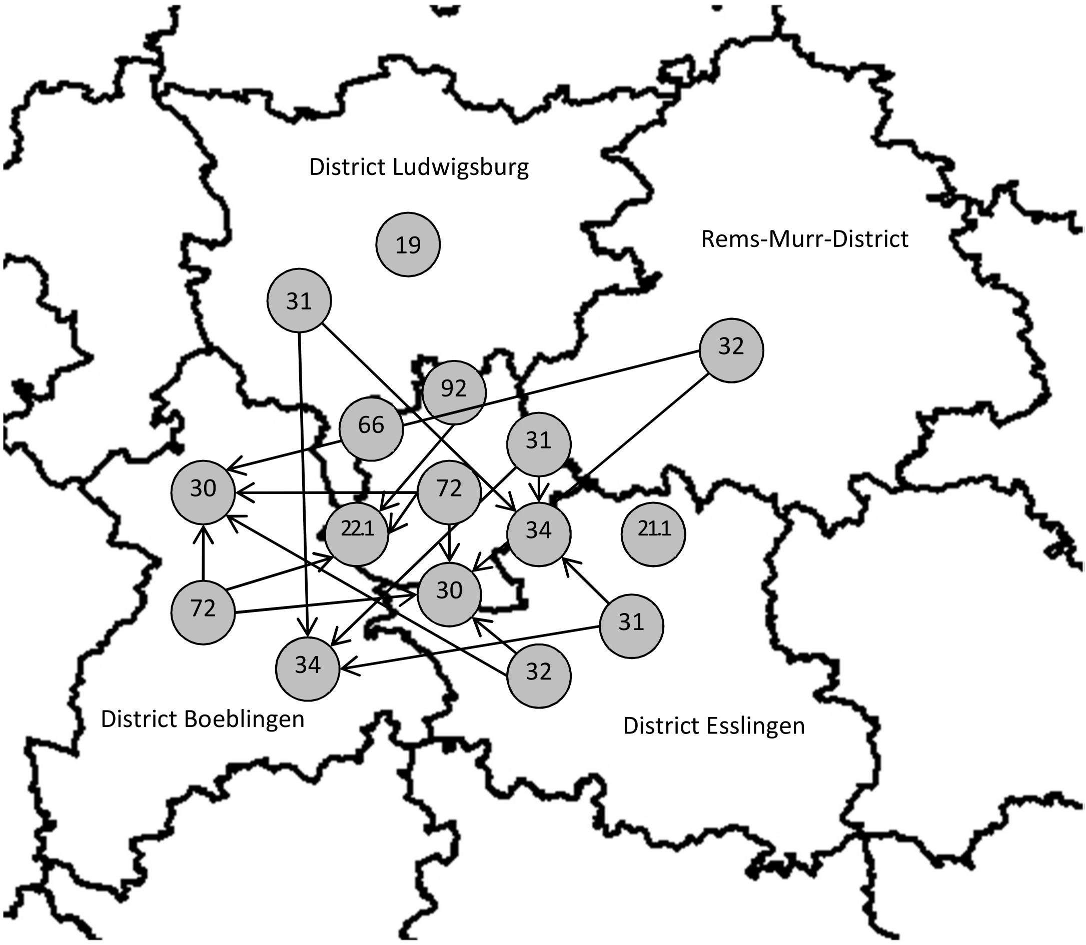
Munich shows strong concentrations specifically in the high-tech manufacturing sectors (NACE 24, 24.4, 30, 31, 34, 35) with substantial inter-industry linkages (see Figure 2-3). These concentrations go along with complementary service sectors, especially research and development IT-services and media, which are strongly interrelated with the manufacturing sectors. Table 2-5 provides further insights into the Munich industry cluster.

Code[a]	Description	Overall		Establishments with more than 500 employees (percentage)		Herfindahl index of employment
		Establishments	Employment	Share of establishments	Share of employment	
16	Manufacture of tobacco products	-	-	100	100	1,000
22.1	Publishing	425	10,206	0	0	0.297
24	Manufacture of chemicals and chemical products	43	3,239	2.3	55.4	0.421
24.4	Manufacture of pharmaceuticals, medicinal	22	1,846	4.5	46.4	0.356
30	Manufacture of office machinery and computers	19	1,427	5.3	87.5	0.770
31	Manufacture of electrical machinery and apparatus	57	23,233	5.3	89.1	0.798
32	Manufacture of radio, television and communication	76	11,611	3.9	91.2	0.834
34	Manufacture of motor vehicles, trailers and semi-trailers	29	38,786	10.3	97.0	0.941
35	Manufacture of other transport equipment	9	5,265	11.1	92.0	0.853
40.2	Manufacture of gas, distribution of gaseous fuels	5	264	0	0	0.845
60.1	Transport via railways	24	5,748	20.8	70.9	0.553
66	Insurance and pension funding	142	24,500	9.2	63.6	0.482
72	Computer and related service activities	1,117	25,362	0.5	35.5	0.224
73	Research and development services	174	5,031	0	0	0.435
92	Recreational, cultural and sporting activities	1,093	17,430	0.5	39.2	0.243
	Total	3,236	175,181			

Table 2-5. Characterisation of concentrated economics sectors in Munich. Note: [a] German classification of economic activities, 2003 edition. This classification scheme bases on the Statistical Classification of Economic Activities in the European Community (NACE Rev. 1.1, see Federal Statistical Office of Germany, 2003 for details). Source: Data used from German Employment Agency, reference date: 30.06.2005; Authors' own calculation.

The number of establishments with more than 500 employees gives an indication of the regional firm structure. Concentrations of several sectors are appearing, as a result of large establishments realising mainly internal economies of scale (NACE 34, 35) with spatial proximate suppliers of vertical linked industry (NACE 31). We can also identify sectors with horizontal and vertical cluster structures marked by a mixture of small, medium and large enterprises (NACE 22.1, 24, 24.4, 30, 32, 73) building up spatial proximate productions networks.

As this first example is limited to the administrative boundaries of the respective region, the concept indicates potential inter-regional transaction flows and the distance between inter-industry linkages. If we extend the regional focus from a small area region (NUTS-3) to the functional area perspective, the industrial network enlarges. Figure 2-4 shows the industrial structure in the functional area of Stuttgart. At district level we find only weak intra-regional interaction, but by increasing the spatial scale the number of inter-industry linkages rises. As the region of Stuttgart is an important production location for the automotive sector (NACE 34), suppliers of electrical machinery and apparatus sector (NACE 32) show concentrations in near-by regions. Furthermore, the IT sector (NACE 30, and especially the service part in NACE 72) was able to establish regional concentrated value chains (see Figure 2-4).



Legend:

19	Tanning and dressing of leather
21.1	Paper and paperboard
22.1	Publishing
30	Manufacture of office machinery and computers
31	Manufacture of electrical machinery and apparatus
32	Manufacture of radio, television and communication equipment and apparatus
34	Manufacture of motor vehicles, trailers and semi-trailers
66	Insurance and pension funding
72	Computer and related service activities
92	Recreational, cultural and sporting activities

Figure 2-4. Structural graph for the functional area of Stuttgart. Source: Authors' own illustration.

With the help of the identified industrial structures we suggest that our approach overcomes limitations of the examination of isolated horizontal clusters by capturing vertical linkages among related industries. Within the cluster framework, three key spillover forces are influencing the economic performance of regions: within clusters, across clusters related by technology or linkages and across common clusters in proximate regions (Delgado et al. 2007). The approach presented allows identifying potential sources of positive spillovers within vertical industrial clusters of a region as same as positive spillovers between proximate regions. These vertical linkages are one of the key sources of cluster-level agglomeration effects and may therefore contribute to growth at the regional level.

2.5 Conclusion and Outlook

In this paper we have presented a method that is suitable for the identification of regional industrial clusters. It is generally acknowledged that these clusters influence regional economic development. Storper and Walker (1989) characterised this phenomenon as 'How Industries Produce Regions', meaning spatial dynamics of industry growth and their effects on regional development. If regional planning agencies assume the cluster concept as a way to promote regional economic growth, it is a necessary first step to identify them with the help of a comprehensive approach. As the formation of clusters is seldom due to the presence of political intent robust measures need to be developed helping to avoid the promotion of too many clusters in too many regions (Sternberg and Litzenberger 2004) However, a standard concept is still required to identify these industrial structures. In the economic literature we can find two ways of analysing cluster structures: input–output analysis, and concentration measures. We suggest combining these two methods. In our analysis we used, first, the minimal flow analysis by Schnabl (1994) for the detection of intermediate relations between certain branches. Then we transformed this structure to the regional level with the help of concentration measures.

With the help of this approach the study is able to overcome the traditional examination of isolated concentrated economic sectors implying that this could be misleading because of the failure to capture vertical linkages among related industries and proximate regions. But these vertical linkages represent two of the three key spillover forces influencing the economic performance of regions: within clusters, across clusters related by technology or linkages and across common clusters in proximate regions (Delgado et al. 2007). In Germany, we found only 11 out of 439 NUTS-3 regions that were characterised by strong vertical clusters. All of these clusters are formed in German agglomerations. Notably, at this spatial scale, only a few regions are able to attract or build proximate production networks. Of course, clusters are not restricted to these administrative boundaries, but the results offer insights about the geographical extent of inter-industry linkages and regional specialisation patterns.

Certainly, applying a national production structure to the regional scale requires making assumptions which are critical. Regions do not usually have the same production structures as the national average nor are regions identically productive. Further Oerlemans and Meeus (2005) point out that local connectivity on its own may even be problematic for firm performance, as firms with both intra- and inter-regional innovative ties with buyers and suppliers tend to outperform other firms in the same sector in innovated processes, products and sales. But the introduced template approach has potential to offer real insights into the regional economic structure. In further research we have to explore the effect of distance on the completion of these benchmark value chains; and we have to identify dynamic changes in cluster structures (the relevance of linkages and regional concentrations of economic sectors). It is self-evident that cluster structures, as well as the whole economy, are subject to structural change. Following this, we have to include cluster life cycles in our analysis and focus on their effects on regional cluster building and regional growth when adding long-term changes in regional intermediate production and inter-industry relations. Up to now, the results have been used as starting points for regional development policies attempting to encourage regional production networks. With the help of the identification of vertical linkages, missing parts of the regional value chain may be highlighted, which can help regional development agencies to understand the relative importance of complementary or related.

Chapter 3

Related variety, unrelated variety and regional functions: A spatial panel approach

3.1 Introduction

The concept of related variety has attracted increasing attention in the discussion on the nature of localised knowledge spillovers and regional growth (Frenken and Boschma 2007, Frenken et al. 2007, Boschma and Iammarino 2009, Bishop and Gripaios 2010, Eriksson 2011, Hartog et al. 2012, for criticism see Desrochers and Leppälä 2011). It questions the hypothesis that Jacobs' externalities per se generate knowledge spillovers and argues that "knowledge will spill over effectively only when complementarities exist among sectors in terms of shared competences" (Boschma and Iammarino 2009, p. 290). The economic rationale behind this argument lies in the notion of sufficient cognitive proximity (Nooteboom 2000). Findings within this context show that large differences in existing and new knowledge prevent effective communications, whilst interactive learning works best when cognitive distance between partners is not too large (Nooteboom et al. 2007). Consequently, this line of thought focuses on the specific regional composition of industrial sectors and splits up the Jacobs externalities argument into the effects of related and unrelated variety (Frenken et al. 2007, Boschma and Iammarino 2009).

This paper resumes this discussion and has two objectives. First, it presents estimates for the effects of related and unrelated variety in Germany from 2003 to 2008. Following studies of Frenken et al. (2007), Boschma and Iammarino (2009), Bishop and Gripaios (2010) and Hartog et al. (2012) we test for respective effects at the level of labour market regions. Second, we pick up recent criticism on the related variety concept made by Desrochers and Leppälä (2011). They point out that sole reliance on industries in the analysis of the composition of a regional economy is debatable, and that it might be more appropriate to analyse localised knowledge spillovers in terms of individual skills or know-how. In line with this thought, we argue that conceptual progress can be made, when we extend the concept of related variety by the role of functions a region performs in the production process (Bade et al. 2004, Duranton and Puga 2005).[5] Koo (2005), Barbour and Markusen (2007) and Currid and Stolarick (2010) for example show that the functions a region performs in the production process can be different for different geographies. This can affect the extent of localised knowledge spillovers economy in two ways. First, a high functional distance or strong functional asymmetry between industries in a region as well as a high cognitive distance prevents effective communication, thus hindering the presence of localised knowledge spillovers (Maggioni and Uberti 2007, Parjanen et al. 2010, Trippl 2010, Lundquist and Trippl 2013). Second, differences in the relative importance of regional functions in the production process may limit the extent of localised knowledge spillovers, as non-routine tasks usually ascribed to headquarter and R&D functions show higher potentials for the generation of knowledge

[5] For a discussion of functional aspects within the context of the ideal types of regional innovation see Lundquist and Trippl 2013).

spillovers (Bade et al. 2004, Duranton and Puga 2005, Robert-Nicoud 2008). To integrate these functional aspects into the concept of related variety, we use an occupation-based approach in conjunction with the industry based analysis. This allows paying attention to the kinds of work the regional economy does as well as to the kind of products it makes (Thompson and Thompson 1985 and 1987, Feser 2003, Koo 2005). Based upon the idea that two regions with similar industry mixes can show differences in the functions performed in those industries (Koo 2005), the simultaneous evaluation of cognitive and functional aspects will allow deeper insights into the nature of localised knowledge spillovers and regional employment growth (Currid and Stolarick 2010).

The paper is structured as follows. The next section identifies main theoretical concepts explaining the sources of localised knowledge spillovers, gives a special focus on the recent related variety debate and presents complementarities between the related variety concept and the role of functions a region performs in the production process. The third section provides insights into the methodologies and variables used to develop an industry-function based related variety concept. Section four presents the results of the model, followed by the concluding remarks.

3.2 Knowledge spillovers and the related variety concept

Localised knowledge spillovers build an integral part of modern theories to explain regional economic growth (Romer 1986). Their very nature, however, has been a controversial issue (for recent reviews of the empirical literature see Rosenthal and Strange 2004, Beaudry and Schiffauerova 2009, de Groot et al. 2009, Melo et al. 2009). Theoretical literature mostly differentiates between three lines of thought. First, the localisation economies approach emphasises the sector specific role of knowledge and skills and argues that the important knowledge spillovers mainly occur within industrial sectors (Marshall 1920, for formalisations see Arrow 1962, Romer 1986). Thus, regional specialisation of economic activities is supposed to be the more innovative and growth enhancing setting (Desrochers and Leppälä 2011). The second approach can be related to the urbanisation economies literature. The existence of urbanisation economies is traced back to external economies based upon the co-location of firms regardless of the industrial sector they belong to (Harrison et al. 1996). External economies are passed on to firms through savings from a dense environment in terms of e.g. population, universities, and public or private research institutes (Malmberg et al. 2000). The third approach can be found in the works of Jane Jacobs (1969). Jacobs puts emphasis on the positive aspects of a diversity of sectors in a region. Her main point is, that a diverse set of regional industrial sectors provides access to different knowledge bases beyond the individual industrial environment (see also Glaeser et al. 1992, Henderson et al. 1995, van Oort 2004). This diversity will spark knowledge spillovers and result in more radical innovations, thus regional diversification is supposed to lead to positive effects on regional economic growth (Frenken et al. 2007, Boschma et al. 2012).

The resulting diversification vs. urbanisation debate has dominated discussion on sources of knowledge spillover in regional science (Beaudry and Schiffauerova 2009). However, recent literature started advocating a more differentiated view on this classic dichotomy. Porter (2003) and Frenken et al. (2007) emphasise the role of relatedness of industries and point out that industrial sectors share commonalities in terms of technologies, knowledge bases, skills or inputs (see also Hildago et al. 2007, Boschma and Iammarino 2009, Eriksson 2011, Neffke et al. 2011). Such types of relatedness are supposed to allow knowledge to spill over more effectively with respective benefits for the regional economy. Relying heavily on the notion of "cognitive proximity" (Nooteboom 2000, Boschma 2005, Nooteboom et al. 2007) Frenken et al. (2007) argue that it is crucial to split up the generic diversity argument and analyse more deeply the specific composition of sectors within the regional economy (see also Boschma and Iammarino 2009, Boschma et al. 2012, Bishop and Gripaios 2010). To disentangle the effects of diversity, they distinguish between related and unrelated variety. Whereas the concept of unrelated variety is likely to capture a portfolio-effect and allows insights into the vulnerability of the regional economy, the related variety concept includes benefits from knowledge spillovers of different but complementary industries in a region (Essletzbichler 2005, Eriksson 2011, Boschma et al. 2012). Thus, the assumption is made that the higher the presence of related industries is in a region, the more opportunities exist for the effective transfer of tacit knowledge (Boschma and Frenken 2011, Eriksson 2011). Coming to the effects of unrelated variety, Frenken et al. (2007) assume that the higher the degree of unrelated variety is in a region, the higher is the ability to absorb sector specific shocks with likewise positive effects on regional growth.

Regarding empirical results, Frenken et al. (2007), Boschma and Iammarino (2009) and Boschma et al. (2012) indeed find that a high degree of related variety has a positive effect on regional economic growth in the Netherlands, Italy and Spain. Additional insights are presented by Bishop and Gripaios (2010) and Hartog et al. (2012). Bishop and Gripaios (2010) show that the impact of related variety is different across sectors with inconsistent signs. Within their study for Great Britain, related variety has a positive effect in only three out of 23 sectors and a negative effect in one. In their study for Finland, Hartog et al. (2012) find that related variety in general has no impact on regional growth. Instead, when controlling for differences in low-, medium- and high-tech sectors, they find that positive effects of related variety are restricted to high-tech sectors. Empirical results for the regional effects of unrelated variety are more heterogeneous. While Frenken et al. (2007) show that unrelated variety is negatively related to unemployment growth and give support to the arguments on vulnerability and shock-resistance, Boschma and Iammarino (2009) and Boschma et al. (2012) only find very little evidence for the portfolio-effect and no other economic effects of unrelated variety. In their sectoral study, Bishop and Gripaios (2010) observe positive effects of unrelated variety on employment growth for eight sectors, whereby these effects seem to be more present in manufacturing compared to the service sector. They finally conclude that the distinction between related and unrelated variety is of importance, but that the effects do differ significantly across sectors.[6]

[6] Boschma and Iammarino (2009) further shed the light on the role of the relatedness of international trade flows on the region. They find that regions benefit from extra-regional knowledge when it emanates from sectors that are complementary to those sectors in the region. However, a likewise study conducted for Spain could not confirm the results (Boschma et al. 2012). Hartog et al. (2012) do not find any significant effects of unrelated variety on annual employment growth.

3.3 The related variety concept and the role of regional functions

Albeit the empirical literature mentioned above has stressed the importance of controlling for the effects of related and unrelated variety, the concept has also received criticism. While focusing on the specific composition of the regional economy with industrial sectors, the related variety concept overlooks the limitations of industrial classifications schemes to reflect individual skills and know-how. Desrochers and Leppälä (2011) make the point that standard industrial classifications (SIC) alone do not capture the variety of channels, through which ideas are used and transferred between industries and suggest that it is more appropriate to analyse the effects of diversification in terms of individual skills and know-how.[7] Hartog et al. (2012) contribute to this point in showing that the effect of related variety on regional growth depends upon certain regional sector specificities such as their technological intensity.[8] However, empirical studies that concern these issues remain scarce.

We argue that conceptual progress in related and unrelated variety literature can be made, when we integrate information about skills via the functions a region performs in the production process. One way to capture individual skills is offered by the analysis of occupations and their respective classification into economic functions (Thompson and Thompson 1985 and 1987, Florida 2002, Feser 2003, Bade et al. 2004, Markusen 2004, Koo 2005, Barbour and Markusen 2007, Currid and Stolarick 2010). This so-called "occupational-functional approach" identifies what specific types of human capital a region possesses, thus is directing attention to the kinds of work the regional economy does (Thompson and Thompson 1985 and 1987, Feser 2003, Koo 2005). With knowledge spillovers being a function of people and respective skills and occupations in a region, this allows clarifying the role of differences in regional functions in understanding localised knowledge spillovers.

The "occupational-functional approach" is able to contribute to the concept of related and unrelated variety in two ways. First, it allows insights into a topic addressed only rarely in the empirical discussion on localised knowledge spillovers: the functional distance or proximity of industrial sectors in a region (Trippl 2010, Lundquist and Trippl 2013). Being at least partially a result of the rise of multi-unit firms increasingly taking advantage of differences in agglomeration, cost and market advantages in varying regions (Chandler 1977, Kim 1999 for theoretical approaches see within the context of the new economic geography and regional functional specialisation see for Duranton and Puga 2005, Fujita and Gokan 2005, Fujita and Thisse 2006, Robert-Nicoud 2008), this strand of literature shows that functions for the same

[7] Additional criticism on SIC based measures of relatedness can be found in the strategic management literature (Bryce and Winter 2009). Albeit this type of analysis focuses on inter-industry relatedness in the context of cross-business synergies of multi-business firms with diverse business portfolios, the arguments against SIC based measures made there also hold for the related variety discussion. This body of literature criticises the use of SIC based measures because these measures do not consistently reflect relatedness among resources, they suffer from varying degrees of breadth in SIC scheme, they implicitly assume equal dissimilarity between different SIC classes, thus perform unsatisfactory when classifying vertically related businesses, they are affected by classification errors, do not consider whether the resources shared could be accessed at an equivalent or even lower cost by non-diversifiers and exclude cases in which two industries are dynamically related (e.g. Rumelt 1984, Barney 1991, Farjoun 1994, Montgomery and Hariharan 1991, Markides and Williamson 1996, Fan and Lang 2000). Tanriverdi and Venkatamaran (2005) further point out that SIC based measures do not allow insights into the types of underlying relatedness as cross-business synergies can arise from the relatedness of certain different functional resources.

[8] In their case, the technological intensity of local sectors is indicated by the presence of low-, medium- and high-tech sectors.

industry can be different for different geographies (for empirical studies see Koo 2005, Defever 2006, Markusen and Schrock 2006, Barbour and Markusen 2007, Currid and Stolarick 2010). These differences in the structure of functions in a region, however, strongly affect the nature and existence of localised knowledge spillovers. Trippl (2010) and Lundquist and Trippl (2013) pick out the functional distance between industries in a region (in their context measured by differences in the innovation performance between regions, in our case more fundamental by the existence and degree of related or unrelated economic functions like R&D, managerial or production tasks) as the major issue in the discussion on ideally types of integrated innovation oriented regional innovation system. They argue that a strong functional distance or asymmetry (or the non-existence of related or unrelated R&D, managerial or production functions in a region) between industries can be seen as a factor limiting opportunities for effective communication and mutual exchange of knowledge (see also Maggioni and Uberti 2007, Parjanen 2010). When the functional distance is too large, knowledge does not flow easily, thus affecting the nature and extent of localised knowledge spillovers. To conclude, functional aspects may spur the effects of related and unrelated variety (Lundquist and Trippl 2013).

A second contribution can found in the literature on the functional specialisation of regions (Bade et al. 2004, Duranton and Puga 2005, Blum 2008, Robert-Nicoud 2008). This strand of literature argues that the functional specialisation of regions leads to spatial differences in knowledge spillovers because headquarter functions and R&D departments show a strong affinity to metropolitan areas (Duranton and Puga 2005, see also Dohse et al. 2005, Davis and Henderson 2008). Differences in the relative importance of regional functions contribute to differences in the content of tacit vs. codified information in regional transactions and thus the amount of localised knowledge spillovers. This view is also advocated by Robert-Nicoud (2008). He discusses the possible range of spillovers arising from routine (dominated by codified knowledge) and complex tasks (characterised by tacit knowledge) and finds it reasonable to assume that routine tasks generate fewer agglomeration economies.

Yet, we argue that the related variety concept can benefit from the integration of functional aspects of the regional economy. The combination of an occupation-based analysis with an industry-based analysis allows drawing attention to the kinds of work the regional economy does as well as to the kind of products it makes (Thompson and Thompson 1985 and 1987, Feser 2003). Based upon the idea that two regions with similar industry mixes can show differences in the functions performed in those industries (Koo 2005), the simultaneous evaluation of cognitive and functional aspects in an occupational-functional approach of the related variety concept allows deeper insights into the nature of localised knowledge spillovers and regional development (Currid and Stolarick 2010).

3.4 Research design

Developing an occupational-functional approach of related and unrelated variety

To develop a framework that is able to reflect cognitive as well as functional aspects of the sectoral composition of a regional economy, we rely on a categorisation of occupations by functions introduced by Bade et al. (2004). Following Duranton and Puga (2001), Bade et al. (2004) differentiate between three broad functional categories (see also Bode 1998). *White*

Collar workers hold executive functions in manufacturing industries but also in service and public sectors. In addition to that, workers holding typical headquarter functions like marketing or providing services related to the existence of headquarters in a region are included in this category. *R&D* occupations are reflected by occupational groups of engineers, natural scientists, agricultural engineers and consultants. *Blue Collar* workers are characterised by diverse manufacturing occupations. Table 3-1 summarises the occupation groups classified into the three different categories.

Categories of occupational functions	Number of occupational group[a]	Description of occupational group[a]
White Collar:		
Managerial and administrative functions	751	Entrepreneurs, Managers, CEOs, Business division heads
	76	Representatives, Employees with administrative or decision making authority
	881	Economists and Social Scientists
	882	Humanist Scientists
Other business-oriented services, Management consultants	752	Management consultants, Analysts
	753	Accountants, Tax consultants
	81	Lawyers, Legal advisors
Marketing	703	Advertising
	82	Publicists, Translators, Librarians
	83	Artists and related occupations
R&D Occupations:		
Technical services, R&D	032	Agricultural engineers and consultants
	60	Engineers
	61	Chemists, Physicists, Mathematicians
	883	Other natural scientists
Blue Collar:		
Manufacturing occupations	07 to 43	Diverse manufacturing occupations in all industries

Table 3-1. Description of the occupational groups that reflect the functions a region performs in production process. [a] According to the nomenclature of occupations, compiled by Federal Statistical Office of Germany in 1970. Source: Own compilation, basic classification developed by Bade et al. (2004). One adjustment is made in the group *White Collar* (additional group 882).

Information about the spatial distribution of occupational functions can be obtained by official statistics. Moreover, the data provided by the Federal Employment Office of Germany within its Social Insurance Statistic allow the combination of an occupation-based analysis with an industry-based analysis and thus the identification of functions performed by an industry in a region. The Social Insurance Statistic builds on the NACE classification of economic activities (Nomenclature générale des activités économiques dans les Communautés Européennes – NACE Rev.1) and combines information about the individual industrial sectoral affiliation down to the five-digit level (1041 industrial sectors), the kind of the individual occupation down to the three-digit level (369 occupational groups) and spatial attributes down to the community level. This high degree of disaggregation allows the simultaneous evaluation of cognitive and functional aspects by calculating function-specific degrees of related and unrelated variety at the regional level. For the purpose of analysis, we aggregate individual data at the level of labour market regions (262 regions). The choice of labour market regions as spatial unit of analysis is based upon arguments made by Eckey et al. (1990). They point out that regions defined on behavioural settings generally perform better than administrative units because the former do reflect economic relations.

Related variety, unrelated variety and regional functions – Calculation of the variety indices

To identify effects of functional proximity (or distance) on regional employment growth, we first calculate function-specific degrees of related and unrelated variety. In line with Frenken et al. (2007), we use entropy at the two-digit level (industrial classification) to calculate the degree of unrelated variety. Related variety is determined by the weighted sum of the entropy at the five-digit level (industrial classification) within the two-digit class.[9] Thus, we assume five-digit sectors sharing the same two-digit sector to experience commonalities fostering learning and facilitating innovative advances (see also Boschma and Iammarino 2009). Information about occupational-functions is taken into account by a division of the general variety indexes into the three categories of occupational functions as stated down in equation 3-1. Thus, we additionally assume that the higher the degree of functional proximity (in *White Collar*, *R&D* and *Blue Collar* functions) in a region, the easier is the communication or interaction between related but also unrelated sectors and the higher are the knowledge spillovers with respective effects on regional employment growth.

The formal calculation from Frenken et al. (2007) changes as follows. If all five-digit sectors *i* of a category of occupational function *j* (where *j* = 1, 2, 3) fall solely under a two-digit sector S_{g_j} (where *g*= 1,…, *G*), it is possible to derive two-digit shares P_{g_j} by summing the five-digit shares p_{i_j}.

$$(3.1) \qquad P_{g_j} = \sum_{i \in S_{g_j}} p_{i_j}$$

The degree of unrelated variety (UV_j) for each of the three categories of occupational functions *j* is calculated by the entropy at the two-digit level.

$$(3.2) \qquad UV_j = \sum_{g_j=1}^{G} P_{g_j} \, log_2 \left(\frac{1}{P_{g_j}}\right)$$

[9] Recent studies mostly assess diversity by the help of inverse Hirschman-Herfindahl index (Henderson et al. 1995, Combes 2000, Combes et al. 2004, Blien and Südekum 2005; for a recent application to Germany see Illy et al. (2011)). However, this does not include related diversity into the analysis (Bischop and Gripaios 2010). The use of the entropy measure is preferred because of its decomposable nature. This allows introducing different digit-level degrees of related and unrelated variety into the regression analysis without causing necessarily multi-collinearity (Frenken et al. 2004) and identifying embedded relatedness of industries within the two-digit level. Avoiding to control for these effects would contribute to an underestimation of Jacobs's externalities because they would be measured as unrelated variety (Beaudry and Schiffauerova 2009).

The degree of related variety (*RVj*) for each of the three categories of occupational functions is defined as the weighted sum of entropy within each two-digit sectors.

$$(3.3) \qquad RV_j = \sum_{g_j=1}^{G} P_{g_j} H_{g_j}$$

with

$$(3.4) \qquad H_{g_j} = \sum_{i \in S_{g_j}} \frac{p_{i_j}}{P_{g_j}} \, log_2 \left(\frac{1}{p_{i_j}/P_{g_j}} \right)$$

Dependent variable

To determine the effects of related and unrelated variety as well as the role of functions performed by regions in the production process, we use annual regional employment growth (*EMPL_GROWTH*) in the manufacturing sector (SIC codes 10 to 41) between 2003 and 2008 as dependent variable. The analysis is conducted at the level of labour market regions. The choice of labour market regions as spatial unit of analysis is based upon arguments made by Eckey et al. (1990). Moreover, their demarcation was confirmed to be suitable in different other studies (Kosfeld and Lauridsen 2004, Kosfeld et al. 2006).

Controls

Specialisation

To test for the effects of regional specialisation, we apply the Herfindahl-Index (*SPECIALISATION*). This measure is defined as the sum of the squares of the two-digit shares P_g of a region *r*.

$$(3.5) \qquad SPECIALISATION_r = \sum_{g=1}^{G} P_{g_r}^2$$

Functional specialisation

The discussion above emphasises the role of the regional functional specialisation in the discussion on localised knowledge spillovers (Bade et al. 2004, Duranton and Puga 2005). We integrate information about the functional specialisation of regions by the ratio of *White Collar* (*WC*) to *Blue Collar* (*BC*) workers in region *r* (*FUNC_SPECIALISATION*).

Size of the regional economy

The size of a regional economy can affect the existence of spillovers effects irrespective of the sectoral composition of the regional economy (Combes 2000). Frenken et al. (2007) for example argue that it is the dense presence of economic, social, political and cultural organisations that influence the emergence of urbanisation economies. This means that the level and quality of spillovers is affected by the number of complementarities between regional organisations (Ó hUallacháin and Satterthwaite 1992, Combes 2000). Combes (2000) further points out that size effects may also negatively influence regional growth through the presence of pollution or transportation congestion. On the basis of recent studies on Germany

(Illy et al. 2011), we measure the size of the regional economy by the employment density of a labour market region *r* (*SIZE*).

Average firm size and human capital

In line with other empirical studies, we integrate two additional independent variables into the regression analysis which are supposed to affect regional employment. This includes the average firm size (*AV_FIRM_SIZE*) and the regional level of human capital (*HUMAN_CAPITAL*). Whilst the first is measured by the average firm size in the manufacturing sector in the respective labour market region *r*, human capital is reflected by the regional share of R&D employees on total regional employees (see Fritsch and Slavtchev 2011 for a similar approach). As same as for the dependent variable, all independent variables are calculated for the manufacturing sector only (SIC codes 10 to 41).[10]

3.5 Model specification

To identify the effects on regional employment growth in the manufacturing sector, we apply a spatial panel approach (Elhorst 2003, 2010). Regional employment growth is expected to be correlated over space. Thus, it has become standard to control for spatial dependence in this context (LeSage and Fischer 2008). Literature distinguishes two basic types of spatial dependence. Spatial lag dependence reflects true (economic) interactions across spatial units. Spatial error dependence refers to measurement problems as a result of the arbitrariness of administrative boundaries of spatial units (Anselin and Rey 1991). Neglecting spatial dependence may act as an omitted variable bias and produce biased results (LeSage and Pace 2009).

The static panel model that we want to estimate takes into account a spatial lag of the dependent variable and spatial autoregressive disturbances and is stated as

$$(3.6) \qquad y = \lambda(I_T \otimes W_N)y + X\beta + u$$

where y describes a *NT x 1* vector of observations of the dependent variable, X is the set of explanatory variables (*NT x k* matrix), I_T is an identity matrix of dimension T, W_N a non-stochastic spatial weights matrix (row-standardised first order contiguity matrix in our case) and λ denotes the corresponding spatial parameter (Millo and Piras 2012). The disturbance vector u is determined by the sum of two terms:

$$(3.7) \qquad u = (\iota_T \otimes I_N)\mu + \varepsilon$$

where ι_T is a column vector of ones of dimension T, I_N an *N x N* identity matrix, μ denotes vector of time-invariant individual specific effects and ε denotes an error term described by:

[10] The descriptive statistics and correlation tables can be found in the Appendices A3-1 and A3-2.

$$(3.8) \qquad \varepsilon = \rho(I_T \otimes W_N)\varepsilon + \nu$$

Spatial-specific effects can be treated as fixed or random effects (Elhorst 2012). Even though the Hausman test allows testing the appropriateness of the fixed or random effects model, recent literature emphasises the suitability of fixed effects models when the "sample happens to be the population" (Beenstock and Felsenstein 2007, p. 178). In this case, spatial specific effects are better determined by fixed effects "because each spatial unit represents itself and not sampled randomly" (Elhorst 2012, p. 10). The fixed effects models further have the attraction that they allow to control for unobserved individual heterogeneity. Such unobserved individual heterogeneity itself is a source of omitted variable bias (Cameron and Trivedi 2005).[11]

We follow the arguments made by Beenstock and Felstenstein (2007) and Elhorst (2012) an estimate a fixed effects model. This model specification also is supported by the Hausman test (see Table A3.3). Table A3.4 in the appendix confirms that spatial dependence is of relevance for our analysis (significant joint test of spatial autocorrelation). The results of the LM test favour a model including a spatially lagged dependent variable. This leads us to conclude that a spatial panel fixed effects lag model is the appropriate model specification for the purpose of our analysis.

3.6 Results

The regression results for the level of labour market regions are presented in Table 3-2. We estimated two different variants of four models. However, all variants of the models show consistent results for the variables applied in this analysis. Model 1 includes only the control variables. Here it can be shown that four out five control variables contribute negatively to regional employment growth. The negative effects of *SIZE* and *SPECIALISATION* are in line with previous research on the manufacturing sector in Germany presented by Blien and Südekum (2005). They are also supported by a recent study of Illy et al. (2011) for an almost similar period in Germany. Therein, Illy et al. (2011) find negative effects of increasing levels of *SPECIALISATION* on regional employment growth at the level of planning regions. Surprisingly, *HUMAN_CAPITAL* and *FUNC_SPECIALISATION* per se contribute negatively to regional employment growth in the manufacturing sector, a fact that will be analysed more deeply in Model 4.

[11] Elhorst (2012) points out that spatial fixed effects can only be estimated consistently when T is large. However, the inconsistency of μ does not affect the estimator the slope coefficients β. As this study is primarily interested in β, an potential incidental parameter problem is of minor importance.

Variables	Variant 1				Variant 2			
	Fixed effects model				Spatial panel fixed effects lag model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
RV		0.026**	0.029**			0.026**	0.028***	
URV			0.034***				0.034***	
RV_ WC				0.015*				0.015**
RV_R&D				0.027***				0.027***
RV_BC				-0.019				-0.019
URV_WC				-0.001				-0.001
URV_R&D				-0.010				-0.010
URV_BC				0.037***				0.037***
SPECIALISATION	-0.176***	-0.189***			-0.179***	-0.192***		
FUNC_ SPECIALISATION	-0.610***	-0.593***	-0.601***	-0.583***	-0.617***	-0.600***	-0.608***	-0.589***
HUMAN_CAPITAL	-1.143***	-1.041***	-1.035***	-1.090***	-1.139***	-1.038***	-1.031***	-1.088***
Log(SIZE)	-0.208***	-0.205***	-0.208***	-0.208***	-0.201***	-0.205***	-0.208***	-0.208***
Log(AV_FIRM_SIZE)	-0.005	-0.009	-0.010	-0.003	-0.005	-0.009	-0.010	-0.003
Λ					-0.054	-0.053	-0.051	-0.039
N	262	262	262	262	262	262	262	262
T	5	5	5	5	5	5	5	5

Table 3-2. Results of the panel regressions on annual employment growth in German labour market regions, 2003-2008. Note: ***, **, * indicate statistical significance on the 1%, 5% or 10% level. Estimations are done with splm package by Millo and Piras (2012). The fixed effects models include individual and time specific effects. Due to the high correlation between the variables *SPECIALISATION* and *URV* (-0,941), we decided to enter variables separately in the models. Source: Authors own calculation.

Models 2 and 3 stepwise include both general variety variables (*RV* and *URV*). We find that related variety (*RV*) as same as unrelated variety (*URV*) positively affect regional employment growth. This is in also line with previous results for effects of diversity in general on regional employment growth in Germany (Blien and Südekum 2005, Illy et al. 2011, Fuchs 2011). However, this is the first study for Germany that explicitly splits up the generic diversity argument introduced by Jacobs (1969) and analyses more deeply differences in regional variety structures. The results give support to the argument that the distinction between related and unrelated variety is of importance (Frenken et al. 2007, Bishop and Gripaios 2010). Furthermore, the results confirm the effects of related variety in likewise studies by Frenken et al. (2007), Boschma and Iammarino (2009), Bishop and Gripaios (2010) and Hartog et al. (2012). In contrast to these studies we also find unrelated variety to have a positive effect on regional employment growth (Bishop and Gripaos 2010).

Model 4 allows deeper insights into the drivers behind the positive effects of related and unrelated variety. It presents the decomposed variety indices that can be differentiated into *White Collar* (*RV_WC*, *URV_WC*), *R&D* (*RV_R&D*, *URV_R&D*) and *Blue Collar* (*RV_BC*, *URV_BC*) functions. The results show, that the drivers behind the effects of related and unrelated variety differ. We find that high levels of related variety in *White Collar* (*RV_WC*) and *R&D* (*RV_R&D*) functions have positive effects on regional employment in the manufacturing sector. In contrast to this, the effects of unrelated variety are found to be significant for *Blue*

Collar functions (*URV_BC*). The results of *RV_WC* and *RV_R&D* can be set in relation the negative results for the *HUMAN_CAPITAL* and *FUNC_SPECIALISATION* variables. It is not the share of engineers on regional manufacturing employment that per se positively affects regional employment growth but rather a high level of relatedness within this functional employment category. The same argument holds for the functional specialisation variable. It is not the relative importance of *White Collar* to *Blue Collar* functions that exerts positive effects on regional employment growth but rather a high level of relatedness within the *White Collar function*. This gives support to the arguments made Trippl (2010) and Lundquist and Trippl (2013). The higher is the level of relatedness in non-routine tasks performed in a region, the higher is the content of tacit information in regional transactions and thus the amount of localised knowledge spillovers with respective positive effects on regional employment growth. Coming to the effects of high levels of unrelatedness in *Blue Collar* or manufacturing functions, the results indicate that regions benefit from diverse *Blue Collar* functions. Theoretical reasons for that can be traced back to arguments such as a large diversified pool of qualified labour as source of knowledge spillovers and regional growth. Such spatial patterns are advantageous to firms as same as workers when workers can move among employers without retooling and firms gain access to a wide set of labour with skills they need (Ellison et al. 2010).

3.7 Conclusions

This paper had two main goals, first to present estimates of the effects of related and unrelated variety on regional growth in Germany from 2003 to 2008 and second to develop an occupational-functional approach of the related variety concept to control for effects of functions a region performs in the production process. Functional aspects are integrated into the analysis by a decomposition of related and unrelated variety indices into three categories of occupation functions (*White Collar*, *R&D* and *Blue Collar* workers). Previous studies only applied an undifferentiated view of the effects of related and unrelated variety or did not test for their effects (Glaeser et al. 1992, Frenken et al. 2007, Boschma and Iammarino 2009 with some exception in Hartog et al. 2012).

Our results support the need for a more differentiated view on variety in the discussion on regional employment growth and highlight the importance of controlling for regional functions in the production process in this context. We find that both related variety and unrelated variety positively affect regional employment growth in the manufacturing sector in Germany between 2003 and 2008. However, it is necessary to shed further attention to the kinds of work a region does in the production process to get deeper insights into the drivers behind these effects. *White Collar* and *R&D* functions are characterised by a non-routine nature and thus, offer much more potential for localised knowledge spillovers (Robert-Nicoud 2008). Our results indicate that related variety acts as an accelerator in this context. The driver behind the effect of unrelated variety is different from those of related variety and can be found in the *Blue Collar* function. This can be traced back to arguments such as positive effects of regional labour market pooling.

This research approach opens up a number of different other issues that further research should shed more light on. First of all, the application of SIC-based measures alone does not sufficiently present insights into the nature of potentials for localised knowledge spillovers. They assume that the functions performed in an industry are similar for different geographies. This is not necessary the case (Koo 2005, Barbour and Markusen 2007, Currid and Stolarick 2010). Future studies could attempt to refine this classification of occupations to achieve more specific insights into the effects of functional proximity/distance or interactions of functions on regional growth. Furthermore, more advanced measures of relatedness are needed. The discussion in the strategic management literature proposes co-occurrence approaches as an appropriate tool in this context (Bryce and Winter 2009). First approaches that integrate these insights into regional science literature can be found in Neffke and Henning (2012). However, relatedness is a multi-dimensional construct and relatedness patterns might be different in different contexts (Bryce and Winter 2009). Thus, future research needs to consider different types of relatedness. While relatedness of products is of importance, for example skill-relatedness (Neffke and Henning 2012) is crucial when coping with increasing needs for flexibility in regional structural change and enabling cross-sectoral knowledge spillovers.

Appendix A3

Variables	Mean	SD	Min	Max
RV	1.85	0.40	0.50	2.71
URV	3.47	0.42	0.89	4.16
RV_ WC	1.51	0.45	0.15	2.51
RV_R&D	1.17	0.48	0.00	2.43
RV_BC	1.79	0.41	0.53	2.77
URV_WC	3.31	0.48	0.37	4.18
URV_R&D	2.70	0.57	0.22	3.93
URV_BC	3.34	0.41	0.86	4.02
SPECIALISATION	0.14	0.08	0.07	0.79
FUNC_ SPECIALISATION	0.06	0.04	0.01	0.41
HUMAN_CAPITAL	0.04	0.02	0.01	0.16
SIZE*	26.66	37.13	1.36	375.83
AV_FIRM_SIZE*	30.46	16.86	10.64	201.01

Appendix A3-1. Descriptive statistics of independent variables (pooled, n=1310).
Note: * SIZE and AV_FIRM_SIZE enter the regression analysis log transformed.
Source: Authors own calculations.

Variables	RV	URV	RV_ WC	RV_R&D	RV_ BC	URV_ WC	URV_ R&D	URV_BC	SPECIALI-SATION	FUNC_ SPECIALI-SATION	HUMAN_ CAPITAL	SIZE	AV_FIRM _SIZE
RV	1												
URV	0.473	1											
RV_ WC	0.858	0.427	1										
RV_R&D	0.832	0.309	0.776	1									
RV_BC	0.960	0.401	0.804	0.805	1								
URV_WC	0.432	0.818	0.389	0.315	0.368	1							
URV_R&D	0.453	0.752	0.392	0.337	0.385	0.704	1						
URV_BC	0.431	0.958	0.398	0.273	0.382	0.734	0.680	1					
SPECIALISATION	-0.437	-0.941	-0.363	-0.261	-0.364	-0.787	-0.679	-0.889	1				
FUNC_	0.085	0.025	0.093	0.055	0.163	-0.253	-0.012	0.116	0.054	1			
HUMAN_CAPITAL	-0.036	-0.079	0.081	-0.035	0.085	-0.227	-0.274	-0.000	0.138	0.708	1		
SIZE	0.119	-0.162	0.256	0.198	0.184	-0.144	-0.091	-0.140	0.195	0.240	0.365	1	
AV_FIRM_SIZE	-0.393	-0.594	-0.232	-0.201	-0.292	-0.528	-0.465	-0.518	0.683	0.172	0.343	0.356	1

Appendix A3-2. Correlation matrix of independent variables (pooled, n=1310). Source: Authors own calculations.

	Model 3		Model4	
	Fixed effects	Random effects	Fixed effects	Random effects
Hausman's χ^2	-	126.4	-	154.6
Df	-	7	-	11
p-value	-	0.000	-	0.000

Appendix A3-3. Results of the Hausman test for spatial models. Notes: Tests are done with splm package by Millo and Piras (2012). Source: Own calculation.

LM tests (Dubarsy and Ertur 2010)	Model 3		Model4	
	LM-Statistic	p-value	LM-Statistic	p-value
Joint test of spatial correlation (H0: absence of spatially correlated residuals and spatial correlation of the dependent variable)	67.64	< 0.01	59.85	< 0.01
Spatial correlation in residuals (H0: absence of spatial correlation in residuals)	27.80	< 0.01	31.02	< 0.01
Spatial correlation of the dependent variable (H0: absence of spatial correlation of the dependent variable)	40.30	< 0.01	41.93	< 0.01
Spatial correlation in residuals when spatial correlation of the dependent variable is accounted for (H0: absence of spatial correlation in residuals)	1.85	0.17	1.51	0.22
Spatial correlation of the dependent variable when spatial correlation in residuals is accounted for (H0: absence of spatial correlation of the dependent variable)	491.87	< 0.01	444.32	< 0.01

Appendix A3-4. LM tests for spatial dependence (fixed effects panel model). Notes: A 262x262 row standardised contiguity matrix is used. The tests developed in Dubarsy and Ertur 2010 are performed via the MATLAB code provided by Debarsy and Ertur for the Econometrics toolbox of LeSage (http://www.spatial-econometrics.com). Source: Own calculation.

Chapter 4

The structure and evolution of inter-sectoral technological complementarity in R&D in Germany from 1990 to 2011

4.1 Introduction

The technological complexity of modern products and services increases the difficulty for organisations to hold all resources needed to sustain their competitive advantages (Harrison et al. 2001). In addition to the need for an effective acquisition, assimilation, and application of knowledge, this contributes to a widespread use of strategic alliances in general and R&D collaboration in particular to enhance organisations' performance (Cohen and Levinthal 1990, Dyer and Singh 1998). Collaborative R&D efforts give access to partner resources, and in many occasions, collaborating organisations may benefit from collective and organisational learning (Teece 1986, Arora and Gambarella 1990, Ahuja and Katila 2001). Partner selection in R&D however "does not occur in a vacuum" (Hitt et al. 2000, p. 449). Collaboration configurations differ in their probability to generate value and sometimes may even induce value-destroying effects (Zajac and Olsen 1993, Madhok and Tallman 1998, Khanna et al. 1998, Das and Teng 2000). Hence, choosing the right partner is crucial in this context. However, what makes the right partner?

The resource-based view (RBV) literature on R&D collaboration seeks to answer this question by identifying resource combinations that offer the greatest competitive advantage (Dyer and Singh 1998, Lavie 2006). Amongst others, the literature suggests that combinations of complementary (knowledge) resources are particularly useful in this respect (Madhok and Tallman 1998, Mowery et al. 1998, Miotti and Sachwald 2003). Complementary resources "*combine effectively with those* [partners] *already have*" (Wernerfelt 1984, p. 175). Given complementary resources, collaborating organisations are likely to develop organisation-specific competitive advantages based on innovation quality and novelty (Dyer and Singh 1998, Chung et al. 2000, Makri et al. 2010). A second perspective emphasises the role of similar partner resources. Resource similarity allows for local search processes on the basis of familiarity with specific technological problems (Nonaka et al. 1996, Stuart 1998). Given similar resources, collaborating organisations are able to create benefits from an easier exchange and combination of knowledge, which may yield positive effects on innovation quantity in similar technology domains (Makri et al. 2010).

Both resource similarity and complementarity are, moreover, building blocks of the relatedness concept (Teece 1994, Farjoun 1998, Boschma and Iammarino 2009). Inspired by insights from the literature on cognitive proximity (Nooteboom 2000) as well as on the theory of recombinant innovation (Fleming 2001), the (knowledge) relatedness concept argues that effective collaboration is enhanced by partners having similar and complementary knowledge. Such ensures effective communication and interactive learning that help to avoid cognitive lock-ins (Nooteboom 2000, Ahuja and Lampert 2001). However, in the literature on relatedness, often a clear distinction between similarity and complementarity as elements of relatedness is missing. As Makri et al. (2010, p. 605) point out: "*Relatedness has commonly been defined in broad terms often using similarity and complementarity interchangeably (i.e.,* *Davis et al., 1992; Farjoun, 1998); others have provided incomplete or tautological definitions of complementarity (Mowery, Oxley, and Silverman, 1998), and a few have ignored it (Lane and Lubatkin, 1998; Ahuja and Katila, 2001)*". This may produce misleading results concerning the determinants and effects of relatedness, as the underlying processes of knowledge integration and application are likely to differ for similar and complementary partner resources. Following Larsson and Finkelstein (1999), Makri et al. (2010) propose a framework that explicitly differentiates (knowledge) relatedness into *technological similarity* and *technological complementarity* and their interaction.

We adopt this perspective and translate it to the context of collaborative R&D. While relatedness is a multi-dimensional construct (Tanriverdi and Venkatraman 2005, Makri et al. 2010), we focus on the complementarity dimension of relatedness within a value chain activity (R&D). The paper has two objectives. Its first objective is to identify empirically systematic inter-sector technological complementarity patterns. In order to accomplish this, we identify technological complementary by means of a survivor-based measure (Teece et al. 1994, Bryce and Winter 2009), which builds on the frequencies of inter-organisational R&D collaborations as indicator. On this basis, we map the so-called *complementarity space* for 129 sectors in Germany showing each sector pair's potential for complementary resource partnering. The paper's second objective is the investigation of complementarity space's structure and its evolution over time. For this, we construct the complementarity space for more than 20 consecutive years and explore its structural change by means of social network analysis. Consequently, we put forward hypotheses concerning the (dynamic) position of certain sectors within the space and the space's general structure. First, this concerns the development of sectors' knowledge integration potential exemplified by the ICT service sector. Second, we hypothesise about and empirically test the presence of community structures within the complementarity sectors.

The paper is structured as follows. Insights of the RBV into resource relatedness, similarity, and complementarity are discussed in the subsequent section. Section 3 outlines the method of measuring inter-sectoral resource complementarity on the basis of collaborative R&D projects. The employed empirical data is introduced as well. The description and analysis of the complementarity space and its evolution are subject to Section 4. Section 6 concludes the paper.

4.2 The RBV, collaborative R&D, and resource complementarity

4.2.1 Resource relatedness, similarity and complementarity

We start from the general point of view that relatedness is supposed to be a key mechanism determining firm strategy and action in various contexts. Empirical work on relatedness frequently builds upon the resource-based view. According to the RBV, resources that are rare, valuable, non-substitutable, and difficult to imitate lie at the heart of competitive advantage (Barney 1991). The RBV characterises firms by differences in their resource positions. Given heterogeneous resource endowments, R&D collaborations enable firms to combine and benefit from heterogeneous resource combinations, which particularly concerns knowledge resources (Nooteboom et al. 2007).

Benefits from R&D collaboration are driven by the value creation potential of pooled resources (Lavie 2006). R&D collaborations enhance organisations' innovation activities and outcomes by allowing full exploitation of internal resources and by extracting relational rents (Dyer and Singh 1998, Lavie 2006). In recent years, in particular, the importance of relational rents has been increasing. Greater R&D collaboration intensity is found to generate positive effects on organisations' survival, growth, and innovative output (Baum and Oliver 1991, Powell et al. 1996). For these reasons, organisations realising R&D collaboration tend to outperform those exclusively relying on internal research efforts (Chesbrough 2003, Schmiedeberg 2008, Hagedoorn and Wang 2012). However, while being primarily related to positive effects, R&D collaboration does bear the potential for loss of valuable resources to partners and negative overall effects on value creation (Hagedoorn and Schakenraad 1994, Stuart 2000, Cassiman and Veugelers 2002). The choice of collaboration partners is the explanation for this seemingly contradictory finding. Positive effects of collaborative R&D cannot be generated with just any partner. To the contrary, they are strongly dependent upon appropriate partner selection, trust, commitment, and proper alliance management (Lambe and Spekman 1997, Ireland et al. 2002, Shah and Swaminathan 2008).

Crucially, R&D collaboration is considered to be especially effective when giving access to similar and/or complementary (knowledge) resources (Powell et al. 1996, Eisenhart and Schoonhoven 1996, Madhok and Tallman 1998, Stuart 1998, Makri et al. 2010).[12] Herein, complementary resource collaborations combine resources that are substantially different (Gulati 1998, Das and Teng 2000). Benefits of such combinations predominantly emerge from external economies of scope (Nooteboom 2000). Complementarity requires a fit of resource sets, which depends upon organisations' mutual cognition of creating value from stepwise converging knowledge resources. Rothaermel et al. (2006) show that organisations, that are able to integrate complementary knowledge, tend to increase their numbers of new products. Complementarity hence induces explorative searches through experimentation with new competencies and technologies. Organisations may be enabled to break with existing dominant designs and routines, which yield positive effects in terms of innovation novelty and quality in new technological domains (Nooteboom 1999, Gilkey and Kilts 2007). However, integrating complementary knowledge is associated with higher efforts and costs as well as higher risks of failure.[13]

In contrast, collaboration based upon similar resources is characterised by benefits of reduced costs and risks through economies of scale (Ahuja 2000, Miotti and Sachwald 2003). In terms of the potential for learning and innovation, resource similarity may foster local searches and the exploitation of what is already known. It thereby supports the emergence of routinized

[12] Resource complementarity matters at different stages of the value chain. While the present paper focuses on resource complementarity in R&D, for instance, Chung et al. (2000) measure complementarity by investment banks' differences in locational (co-location) and sector strengths (shared clients). Wassmer and Dussauge (2012) define resource complementarity in terms of increases in served city pair markets when different airlines enter an alliance. Lin et al. (2009) use the standard industrial classification (SIC) system to define complementarity, which is given when alliance partners do not share the same four-digit SIC code. Wang and Zajac (2007) study complementary production processes by using co-occurrences of four digit NAICS codes at the firm-level.

[13] Another form of resource combinations can be seen in the pooling of unrelated resources. This bears potential for most radical innovations. However, because of lacking absorptive capacity between collaboration partners, innovations in this case are much more unlikely in comparison to combinations based upon complementary resources (Boschma and Iammarino 2009, Makri et al. 2010).

learning and the potential of significant path dependencies (Nooteboom et al. 2007). The relatedness concept allows integrating both strands – partner resource similarity and complementarity – into one powerful framework. It is argued that performance is conditional on collaborating partners being characterised by related cognitive structures and (knowledge) resources (Boschma and Iammarino 2009). The relatedness concept highlights the fact that absorptive capacity (similarity) alone may not be sufficient to benefit from new knowledge but rather by access to *"knowledge that is complementary, but not similar, to existing competences … will particularly enhance interactive learning"* (Boschma and Iammarino 2009, p. 295). Hence, relatedness implies both similarity as well as complementarity, whereby complementarity depends upon fit and determines the potential for generating (new) knowledge in new technological domains. In contrast, similarity defines partners' mutual absorptive capacities and the generation of new knowledge in similar technology domains (Makri et al. 2010, D'Este et al. 2013). However, this distinction is rarely made explicit in the literature on (knowledge) relatedness. Common definitions of relatedness, as mentioned in the introduction, rather make use of interchangeable applications of both notions, ignoring their distinctiveness (Makri et al. 2010). This causes a problem in the empirical identification of relatedness' determinants. For instance, it remains unclear what knowledge resources are to what extent complementarity and allow resource integration. Do similarities enhance absorptive capacities? What about the joint presence of similar and complementary resources? The lack of clarity indicates that the concept of knowledge relatedness can benefit from a more differentiated view on partner resources in collaborative R&D.

4.2.2 Resource complementarity and similarity defined

The focus of this paper is on technological complementarity in R&D. In line with Bryce and Winter (2009), we argue that the RBV is correct in the assessment of forces influencing the directions of organisational alliances such as R&D. Accordingly, we assume that patterns of organisational alliances and collaborative R&D are shaped by the logic of economic efficiency, implying that it is based upon the value creation potential of pooled resources (Das and Teng 2000). The effectiveness of resource pooling is driven by relational rents extracted from knowledge relatedness. The driving forces behind *knowledge relatedness* are *technological similarity* and *technological complementarity* and their interaction. A definition of technology complementarity is provided by Makri et al. (2010, p. 605f.):

- *"Technology complementarity between firms is the degree to which their technological problem solving focuses on different narrowly defined areas of knowledge within a broadly defined area of knowledge that they share."*

This definition allows for analysing technological complementarity from both a dyadic and a portfolio perspective. At the dyadic level, complementarity indicates the relative integration potential across defined areas of knowledge. In our case, we apply sectoral boundaries because of the importance of new knowledge inputs for organisations' R&D activities. This focus on the inter-sectoral dimension is in line with several taxonomies of sectoral patterns of innovation that capture inter-sectoral linkages in terms of complementarities in knowledge production (Pavitt 1984, Miozzo and Soete 2001, Castellacci 2008). Castellacci (2008, p. 980), for instance, argues that "vertical linkages, i.e. the set of relationships and interactions that innovative firms have with enterprises in other sectors of the economy […] constitute a factor crucial to enhance the competitiveness of whole national [innovation] system" The inter-sectoral integration potential may thereby vary among industries depending on how much their competitive advantages rely upon knowledge of organisations in other industries (Malerba et al. 2013). Herein, differences in sectoral innovation modes might be crucial. For example, Pavitt (1984) identifies supplier-dominated, scale-intensive, specialised supplier, and science-based innovation modes in this context.[14] These highlight the type of linkages industries need to strengthen to create benefits related to inter-sectoral knowledge diffusion.

The alliance portfolio or network perspective additionally argues that complementarity may not only be given at the dyadic level of R&D collaboration, but that it is a function of organisations' total collaboration portfolio (Parise and Casher 2003, Wassmer and Dussauge 2011). In this context, the notion of *resource completeness* has been put forward. Resource pairs may not be complements by their own nature, but by virtue of the presence of additional resources being or not being part of two partners' resource sets (Ennen and Richter 2010). Accordingly, these partners may need to collaborate (jointly) with additional organisations to make full use of their resources. In many cases, this will imply that organisations of multiple sectors join in alliances and collaboration in order to realise resource completeness. We can therefore expect groups of sectors to exist, that mutually share technological complementarities, a view that is widely accepted in the literature on national systems of innovation. Given the continuous emergence and diffusion of new technological paradigms, this literature argues that the opportunities and constraints such paradigms offer for joint value creation are influenced by the web of vertical linkages connecting sector-specific regimes and technological trajectories constituted within national system of innovation (Castellacci 2008),

It also needs to be pointed out that the notion of technology complementarity is inherently dynamic. A static notion assumes that collaboration has no effect on complementarity, which ignores the co-evolution of collaboration and technology complementarity (Baum et al. 2010). Hence, insights into the dynamics of technology complementarities are crucial for understanding patterns of R&D collaboration. Advancing the knowledge about these is the main goal of the present paper.

4.2.3 R&D collaboration as indication of technology complementarity and empirical hypotheses

So far, we have outlined how complementarity relates to the performance of collaborative R&D. Now, we'll argue that information on R&D collaboration can be used to approximate technological complementarity. The reason for this is that inter-organisational learning starts when organisations' resources are exchanged, brought together, combined, and jointly exploited (Nooteboom et al. 2007). This is precisely what is at the heart of formal R&D

[14] This is not to say that knowledge flows are restricted to R&D. Technology diffusion comes along disembodied and product-embodied paths. Disembodied diffusion refers to the transmission of ideas and knowledge and can be studied by collaborative R&D or patent-citation matrices (Nomaler and Verspagen 2008). Product-embodied diffusion highlights purchased goods as carriers of technology flows. Given this, Sakurai et al. (1997) found evidence that ICT plays a major role in the generation and acquisition of new technologies. Papaconstantinou et al. (1998) highlight the idea that innovations are developed mainly in clusters of R&D intensive manufacturing industries with service sectors being the main users of technologically sophisticated machinery and equipment. Both aspects will also receive further attention in this paper.

collaboration (Broekel and Graf 2012). While organisations may attempt a large number of collaborations because of costly resources, only the most promising (in terms of returns) will be realised. In other words, it can be argued that activity patterns of inter-organisational collaboration are subject to the survivor principle (Stigler 1958).

The survivor principle, applied in this context, assumes that in a world of scare resources competition between different potential R&D collaboration projects will select the more efficient ones to be realised. In other words, competition among rivaling alternatives eliminates inefficient collaboration attempts. The actually observed collaboration patterns (i.e. those that are realised) are positively evaluated combinations of resources, skills and knowledge that are unevenly distributed among collaborating organisations. This is, however, not to say that all realised collaboration are efficient or even the most efficient ones (Stigler 1958). Results of R&D are uncertain and organisations operate in dynamic environments making miscalculations and mistakes in their choice of appropriate partners and technology domains quite likely. For this reason, we will not evaluate individual organisations' collaboration patterns, but focus on the aggregate sector level, which we assume will average out distortions in the results of the survivor principle at the organisational level. Accordingly, the sectoral level allows for abstracting from contextual factors that might be present at the level of the individual organisations. It moreover allows for mapping the complete R&D *complementarity space*, i.e. the knowledge integration potential among all sectors in an economy.

While it is difficult to make any predictions about the strength of two particular sectors' complementarity relation or even the structure of the complementarity space, the above arguments allow for making at least two expectations. These expectations will be used as a benchmark for an evaluation of the empirically constructed complementarity space. We pointed out that technology complementarity is dynamic. Over the last two decades, the so-called "information and communication technologies (ICT) revolution" (Brusoni et al. 2005) has lead to an explosion of the range of application and usability of ICT and its services throughout almost all sectors of the economy. We therefore expect that the ICT revolution is visible in the complementarity, as the resources of ICT and ICT services should have dramatically increased in (average) complementarity since the 1990s.

> Hypothesis 1: ICT and ICT Services have become more central in the complementarity space over time.

The second hypothesis is derived from the discussion of the portfolio/network perspective on technological complementarity in Section 0. We argue that, frequently, resources of more than two sectors need to be combined in order to achieve resource completeness or at least to increase the efficiency of collaborative R&D projects. If this is the case, the complementarity space will be characterised by a community-type structure that shows as groups of sectors, whereby highly complementary relations exist within groups, but less so among sectors as parts of different groups.

> Hypothesis 2: The complementarity space is fragmented and shows a community-type structure with sectors belonging to the same community offering highly

complementary resources and sectors that are part of different communities being characterised by lower complementarity.

4.3 Empirical approach and data

4.3.1 Operationalising sectors and technological complementarity

In order to identify technological complementarity in R&D, we first have to define areas of technological knowledge such that inter-organisational collaboration potentially corresponds to the idea of complementary resources. In a common manner, we make use of the standard industrial classification NACE and its hierarchical structure for this purpose allowing for differentiating between inter-sectoral and intra-sectoral R&D collaboration (Malerba et al. 2013). In line with the above definition, we generally measure technology complementarity by means of inter-sectoral R&D collaboration existing between organisations classified into different 2-digit NACE codes. Note, however, that in a number of instances, alternative sectoral definitions have to be used (see below). Accordingly, intra-sectoral collaboration corresponds to collaboration among organisations within the same 2-digit NACE code. Intra-sectoral collaboration is excluded from the analysis because, due to the majority principle in the NACE code system, such collaborations will per definition rely to a large extent on similar resource combinations and cognitive proximity. This implies that they involve similar as well as complementary resources, which cannot be differentiated and therefore have to be excluded to avoid biases.

4.3.2 Data on R&D collaboration

To construct the technological complementarity measure, we employ a database on subsidised R&D projects of German organisations. More precisely, the database covers the majority of projects subsidised through support programs of the Federal Ministry of Education and Research (BMBF). In addition, a considerable number of projects that were granted support by the Federal Ministry of Economics and Technology (BMWi) and the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) are included as well. Comprehensive information on these projects is published in the so-called "Förderkatalog" (subsidies database),[15] which lists detailed information on more than 150,000 individual grants supported by the above ministries between 1960 and 2011. For the empirical assessment, we only rely upon the years 1990 to 2011 in which 62,714 projects split into 103,411 individual funds were granted to 30,116 German organisations. The exact start and ending data as well as the magnitude of the granted fund are given for all projects. Moreover, all funds are classified according to an internal hierarchical classification scheme developed by the German Federal Ministry of Education and Research (BMBF) called "*Leistungsplansystematik*". The 16 main areas, which include biotechnology, energy research, sustainable development, health and medicine, are disaggregated into a varying numbers of sub-classes. These are considerably fine-grained. At the highest level of disaggregation (6-digits) almost 1,500 unique research areas can be distinguished.

[15] http://foerderportal.bund.de/foekat/jsp/StartAction.do .

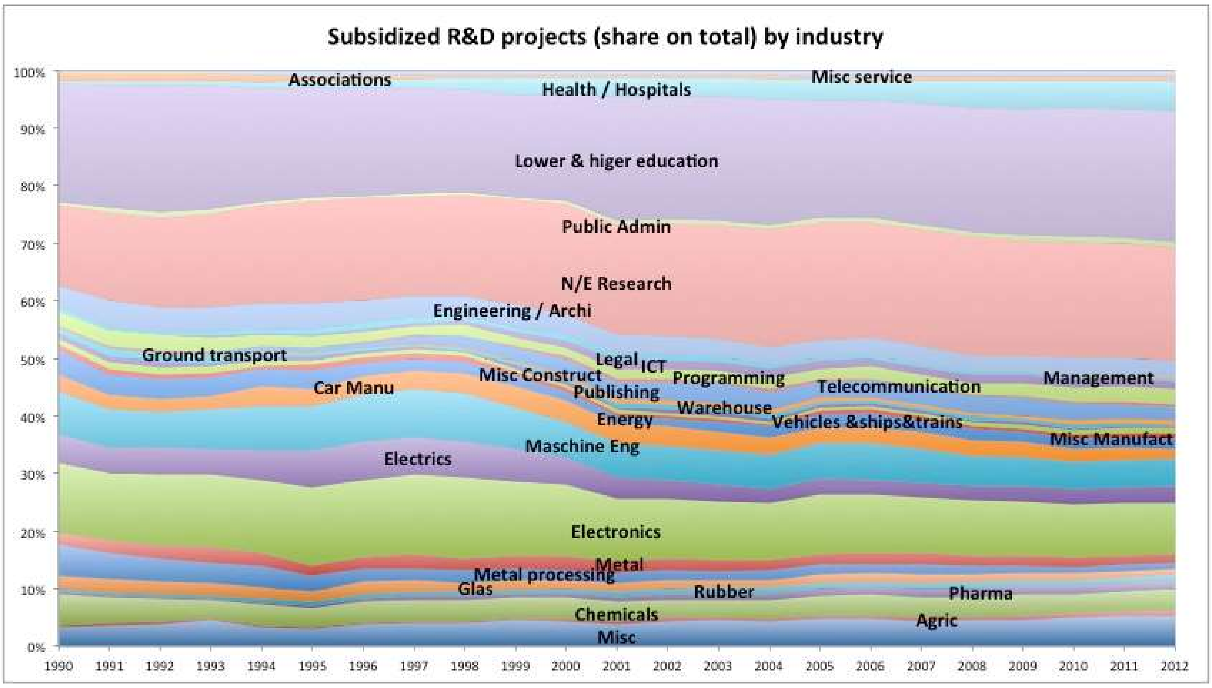


Figure 4-1. Subsidised R&D projects per sector.

The data also include information about the NACE sector class for each organisation allowing for the construction of populations of organisations for each sector. As pointed out above, we define sectors at the 2-digit NACE level. However, in some instances, 2-digit classes summarise extremely heterogeneous activities and organisational types. For this reason, a number of sectors remain disaggregated at the 3-digit level. This particularly concerns educational and administrative activities of the public sector for which the industrial classification is highly aggregated at the 2-digit level. For instance, it is differentiated between universities of applied sciences ("*Fachhochschulen*") and universities ("*Universitäten*"). The *Manufactures of other transport equipment* (C30) are split into the *Manufactures of ships* (C301) and the *Manufacturers of railroad vehicles* (C302), *Manufactures of other transport vehicles* (C303), and *Manufactures of miscellaneous vehicles* (C309). Notably, the class *Scientific research and development* (M72) remains disaggregated into *Research and experimental development on natural sciences and engineering* (M721) and *Research and experimental development on social sciences and humanities* (M722).

Figure 4-1 shows the changing distribution of R&D subsidies across sectors. It highlights one of the specifics of the employed data: in contrast to patent data, the data cover the full set of economic activities and implying that manufacturing is less prominent. The statistics underline the prominent role universities and universities of applied science play in the German subsidisation programs. This is primarily related to the fact that universities represent aggregated organisations made up of a number of faculties and institutes active in very heterogeneous research areas. As this is likely to bias our results and given the usually rather limited interaction among a university's faculties and institutes, we disaggregate universities and universities of applied science into smaller units. To apply a universal disaggregation independent of the organisational structure of these organisations, we split them according to the following twelve research areas: engineering, administration, architecture, natural sciences, art, economics, social sciences, medicine, law, psychology, sport, and miscellaneous.

The disaggregated universities and universities of applied science extend the analysis to 130 sectors. However, we exclude Extraterritorial activities due to their unspecific nature, leaving us with 129 sectors. The complete list of considered sectors is shown in A4-1 in the Appendix.

The database also includes information on whether funds were granted to joint projects that are realised by consortia of organisations ("*Verbundprojekte*"), or whether they supported individual projects conducted by a single organisation. Participants in joint projects agree to a number of regulations that guarantee significant knowledge exchange between the partners. Broekel and Graf (2012) argue, therefore, that collaborative relations exist between all organisations participating in the same joint project. We argued above that, under the assumption of the survivor principle (Stigler 1958), realised R&D collaborations are good indicators for technology complementarity. The idea of the survivor principle still seems appropriate in the case of subsidised R&D collaboration, as we only observe R&D collaboration that have been (externally) evaluated and got awarded with a subsidy grant. All R&D collaboration that failed in the evaluation remain unobserved, which (positively) biases the data towards the most promising R&D projects, i.e. those that "survive" the selection process.

Obviously, this data is subject to political will and subsidisation preferences, as the granting of subsidies is by and large a political process. It implies that subsidies are intended to stimulate public and private research in fields that are politically desirable. In Germany, this particularly applies to new technologies and so-called key technologies that are foremost supported (Fier 2002). Accordingly, the database is subject to a *"political bias"*. The first bias shows as sectors being identified as offering complementary resources because, in comparison to their (real) weights in the economy, they receive an over-proportional share of R&D subsidies. Figure 4-1 highlights this by showing the distribution of (project-based) R&D subsidies over all sectors. A similar bias may occur when joint projects are more frequently supported in some research areas than in others. We control for these potential sources of biases in the construction of the corresponding measures, which will be explained below.

Another potentially biasing effect is related to the fact that the design of R&D subsidy schemes is about choosing which "technologies" are to be supported rather than which sectors. This being said, it means that our indicators are less generalisable if policy primarily supports niche technologies that do not reflect the full spectrum of the technologies applied in the economy. Such niche technologies are inasmuch a problem as they make co-occurrences of sectors in the same technologies less likely. However, when looking at the distribution of the 129 sectors across the 62,714 projects belonging to more than 1,164 technologies ("Leistungsplansystematiken") such cannot be confirmed. Figure 4-2 highlights that about half of the projects are classified into technologies in which at least 15 different sectors are active. Most research areas, and in particular those that account for the majority of projects, are therefore rather general in nature and are applied in multiple sectors.

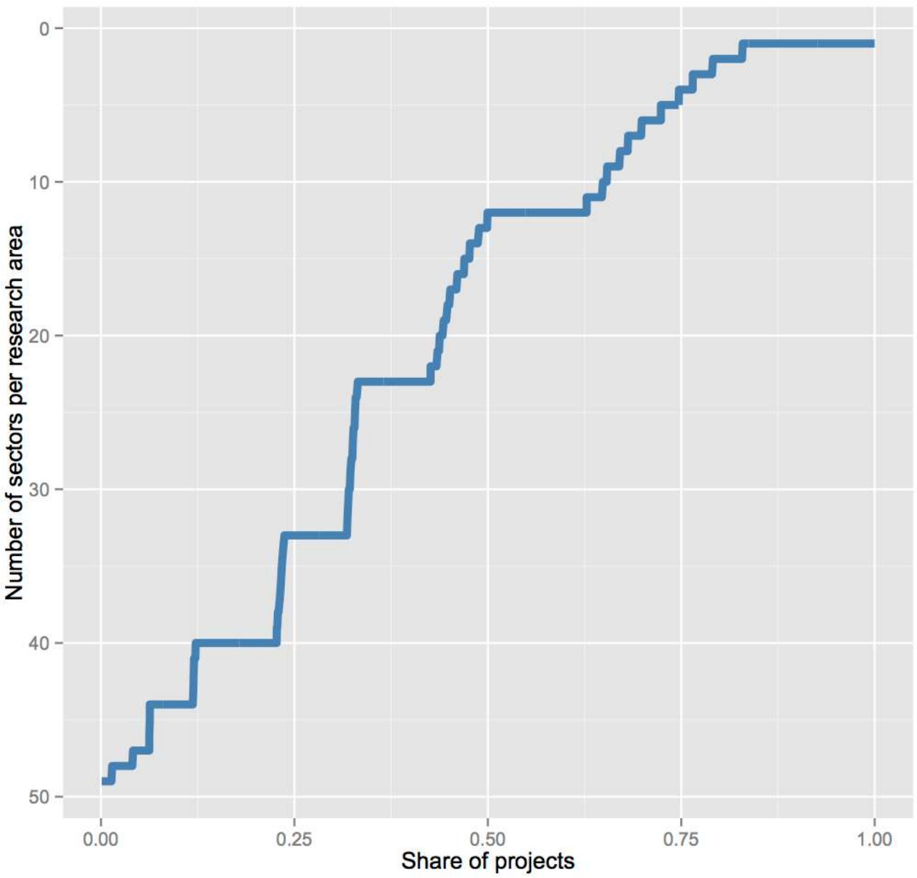


Figure 4-2. Distribution of projects across sectors.

Accordingly, most of the observed technologies are not niche technologies. However, it goes without saying that policy primarily supports technologies that are perceived to bring scientific and economic benefits for their country in the future. We argue, therefore, that our data cover the structures of technological complementarity in R&D right at, or at least near, the technological frontier. In this respect, the data are comparable to patent data, which could be used in a similar fashion to construct the complementarity measure put forward below. The use of patent data is, however, only feasible for sectors for which patents represent a significant mechanism for protecting intellectual property. Service sectors and the like do not patent at all; the same is true for the construction and agricultural sectors. Hence, while our data are clearly subject to some sorts of political bias, we are convinced that this bias does not share the biases to which patent data are subject.

Figure 4-3 reveals that slightly more 65 percent of the 129 sectors are characterised by their organisations being active in at least 25 projects between 1990 and 2000. This number decreases to about 50 percent for the period 2001-2011. Hence, the distribution of the number of subsidised projects across sectors is substantially left-skewed.

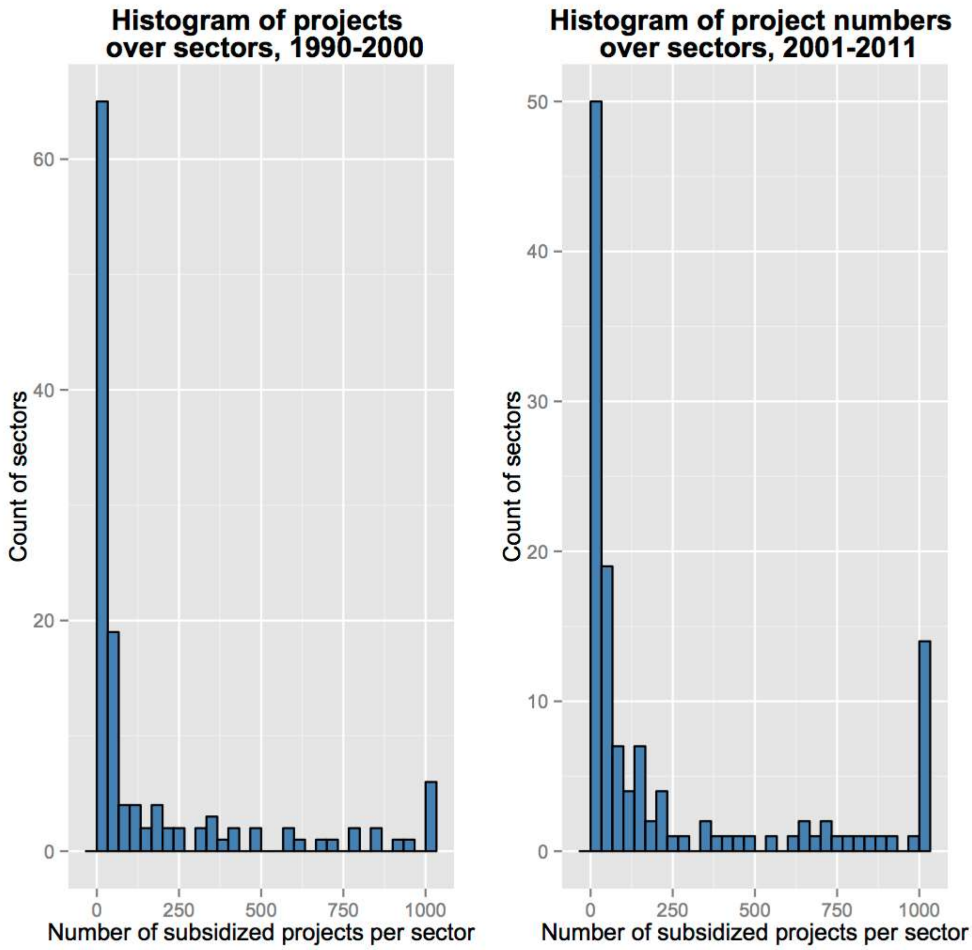


Figure 4-3. Distribution of subsidised R&D projects across sectors.

4.3.3 Indicator of technological complementarity

For the construction of the technological complementarity index we follow the approach by Teece et al. (1994) and consider some refinements proposed by Bryce and Winter (2009). However, given our aim and the type of empirical data, some additional modifications are necessary. As previously put forward, we start from the idea that the frequency of R&D collaboration between organisations belonging to different sectors indicates the extent to which the sectors offer complementary R&D resources for the other. All sectors lacking positive collaboration counts with other sectors are excluded from the sample. According to the above, we also leave intra-sectoral collaboration aside.

On this basis and in close resemblance of Teece et al. (1994) a simple resource complementarity indicator can be constructed by counting the number of co-occurrences of two sectors (e.g. their organisations) in R&D collaborations. This number is defined as J_{ij} being the number of collaborative projects in which at least one organisation of sector *i* and one organisation of sector *j* are jointly participating (see also D'Este et al. (2013) for a similar approach). The raw number of co-occurrences will naturally increase with the number of active R&D collaboration organisations of sector *i* and *j*. It therefore needs to be adjusted with the number of co-occurrence that can be expected if sectors were randomly assigned to organisations active in collaborative projects. Such can be accomplished by estimating the difference between J_{ij} and the expected value of co-occurrences. In the calculation of the latter, K is the number of collaborative projects and n_i represents the total number of projects in which organisations of sector i are participating and n_j the corresponding number for sector j. The expected number of projects in which sector i and j are jointly active (x_{ij}) can be seen as hypergeometric random variable, which shows the following (Bryce and Winter 2009, p. 1575f.):[16]

$$(4.1) \quad P\left[X_{ij} = x\right] = \frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}}.$$

Its mean can be calculated as

$$(4.2) \quad \mu_{ij} = E\left(X_{ij}\right) = \frac{n_i n_j}{K},$$

and its variance by

$$(4.3) \quad \sigma_{ij}^2 = \mu_{ij}\left(1 - \frac{n_i}{K}\right)\left(\frac{K-n_j}{K-1}\right).$$

Finally, the difference between J_{ij} and the expected value μ_{ij} is estimated and standardised.

$$(4.4) \quad \tau_{ij} = \frac{J_{ji-}\mu_{ij}}{\sigma_{ij}}$$

The obtained index τ_{ij} is based on "*raw*" counts of R&D collaboration between two sectors' organisations. In a next step, we standardise τ_{ij} scores. To allow for easier interpretation and to avoid size biases, we standardise the index and subsequently divide the result by the maximum complementarity score. As negative values imply strong non-complementarity and hence are from their meaning identical to zero values, we set these values to zero. The final complementarity index C_{ij} ranges between 0 and 1 with values close to one indicating maximal technological complementarity.

In contrast to Teece et al. (1994) and Bryce and Winter (2009), we do not consider indirect relations between sectors to construct the complementarity score. Indirect approaches compare the complete profile of two sectors' co-occurrences with all other sectors. So, let M be the matrix of co-occurrence, the direct approach exclusively considers the "*direct*" frequency of co-occurrence between sector i and j, i.e. only cell [*i,j*] of M is taken into account. In indirect approaches, in addition to the direct co-occurrence frequency of i and j, the sectors' co-occurrences with other sectors are taken into consideration as well (for a discussion see, Eck and Waltman 2009). In light of the comparatively high level of sector aggregation, we rather use a direct approach and, hence, avoid making the (potentially wrong) assumption that indirect relations contain valuable information on inter-sector resource complementarity. Moreover, considering indirect relations increases the probability of a size

[16] However, this method also has drawbacks, as the quantity J_{ij} might not generally be valid to detect possible deterministic effects. It can attain abnormally high values when purely random processes are present as well as when occupancies are very heterogeneous. A second drawback concerns the random assignment of firms to activities. Assigning a random set of firms to each interaction, which in magnitude is equal to the actual number of associated firms in the data, does not correspond to a unique random association mechanism between firms and activity fields. See for a possible solution Bottazzi and Pirino (2010).

bias because large sectors are more likely to cooperate with a larger number of other sectors than small sectors.

The estimations provide a matrix for each year, which includes relational information about technological complementarity in terms of R&D. The matrices represent kinds of adjacency matrices, which are well-known in social network research (Wasserman and Faust 1994). To describe and analyse the space, we roughly follow Baum et al. (2010) and apply methods of social network analysis.

4.4 Empirical resource complementarity and complementarity space

4.4.1 Testing the indicator's reliability

Some basic characteristics of the obtained complementarity space are shown in Table A4-2 in the Appendix. It is also visualised for the year 2010 in Figure 4-4. However, before looking in detail into the empirical results it is important to evaluate their reliability and trustworthiness. The most important information in this respect is to what extent the results are driven by policy preferring to support particular technologies and sectors. If such is the case, sectors that mainly benefit from policy support will hold central positions in the complementarity space. A sector's centrality is described by two common centrality measures (Freeman 1979, Wasserman and Faust 1994). The first one is a sector's degree centrality, which measures the intensity of direct relations to other sectors, i.e. it can be seen as a measure of centrality in its direct / local neighbourhood in the complementarity space. It is simply estimated by summing the weights of all its direct relations. The second measure, betweenness centrality, captures a sector's position within the entire complementarity space and refers to the frequency of a sector being part of the weighted *shortest path* between any sector pairs. In other words, sectors with high betweenness centrality "*connect*" otherwise distant parts in the complementarity space, i.e. they keep (other) sectors connected. The estimated sector centralities are rank-correlated with the number of subsidised collaborative projects in which the sectors' organisations are engaged (see Table A4-3 in the Appendix). The correlations are positive and significant at the 0.01 level. However, they rarely exceed 0.7. It implies that, while we are controlling for sectors' engagement in collaborative subsidisation programs, there still seems to be a positive relation between support intensity and sectors' centrality in the complementarity space.

There are multiple explanations for this finding. The first one suggests that pairs of sectors that both receive strong support are more likely to obtain high complementarity values. This is, however, not the case. The third column in Table A4-3 in the Appendix shows the corresponding rank-correlation, which reaches a maximum of 0.32*** in only one instance. The second potential explanation is that sectors strongly engaged in collaboration offer valuable resources for other sectors, as it takes "*two to tango*". Accordingly, in order to obtain a central position in the complementarity space other sectors must evaluate this sector's resources as being complementarity to their own, which resembles the idea of resource complementarity. The third explanation refers to the case that policy preferably supports "*bridging*" technologies that connect particular pairs of sectors and hence designs support programs accordingly. Such a pattern is also very much in line with our argumentation. In this case, policy's preferences enforce the survivor principle of observed collaboration. Whether these preferences are more (less) informative or more (less) biased than what can be expected without policy intervention is beyond the scope of the present paper. It is, however, surely an interesting issue for future research. In the light of this, we conclude that the (policy-shaped) distribution of subsidies across sectors has only limited effects on the derived complementarity indicator.

Another sign of quality is the indicator showing some but not too much time variance, since we expect the underlying complementarity structures not to change significantly in the short-run. We test this in two ways. First, we compare each year's complementarity space matrix with that of the next by means of a Mantel's test based on Spearman rank-correlation. Second, we estimate the year-by-year correlations of the two centrality measures. The results are shown in Table A4-4 in the Appendix, which reveals only minor year-by-year variation according to the Mantel test and similarly small changes in the degree centrality scores. The differences in betweenness centrality are more severe, though. This particularly applies to the period from 1998 to 2010 in which the rank correlation of subsequent years' betweenness centralities drops to values lower than 0.4. There is a simple explanation for this. As we will show later, the average complementarity increases over time, causing the complementarity space to increase in density as more relations obtain positive values. This effect simultaneously impacts more or less all sectors, implying that their ranking of degree centralities remains unaffected. However, it also creates additional paths through the network (complementarity space) that alter sectors' global positions in the network, i.e. change their betweenness centrality over time. We conclude from this that the indicator as such is relatively stable over time. However, the increasing integration of the complementarity space causes notable disturbance in sectors' betweenness centrality ranks.

4.4.2 General characteristics of the complementarity space

4.4.2.1 The centrality of sectors

Figure 4-4 shows the complementarity space for Germany in 2010 with the nodes indicating sectors. Not surprisingly, the plot highlights the prominent role the education sector plays in the complementarity space. There are three reasons for this. First of all, due to the division into fields of study, the education sector amounts to about one quarter of all sectors (33) in the analysis. Second, the education sector does not only represent a dominant number of sectors, it also accounts for the largest share of projects on the total number of subsidised R&D projects (see Figure 4-1). Third, the higher education sector and herein in particular the engineering and natural science based fields (University engineering, University natural sciences) offer a wide range of R&D resources that are complementary to other sectors. This translates into these sectors holding central positions in the complementary space. While Figure 4-2 already gives an impression on the centrality of sectors, more precise information is listed in Table 4-1 and Table 4-2 showing the top-ten sectors in terms of degree centrality and betweenness centrality, respectively, in the complementarity space in different years.

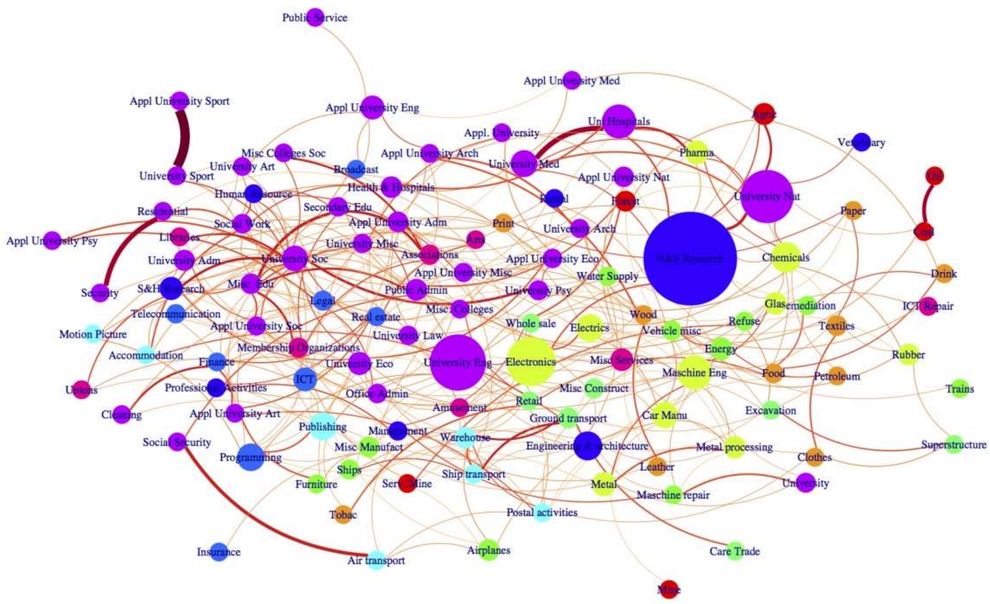


Figure 4-4. Complementarity space in 2010.[17]

In 2010, in particular sectors of (higher) education (*Universities social sciences*, *Miscellaneous education*, *University natural sciences*) obtain large values in degree centrality measures. Among the non-education related sectors, intense non-random ties to their adjacent sectors characterise the sectors *Research natural sciences & engineering (N&E)*, *Research social sciences & humanities (S&H)*, and *Public administration*. Their large degree centrality scores signal, that on the one side, organisations in these sectors provide complementary resources in terms of R&D to a large pool of other sectors. On the other side, organisations operating in this field are characterised by larger heterogeneity of sectors in their R&D collaboration network where they find complementary resources for R&D.

In contrast to degree centrality, being central in the complementarity space in terms of betweenness implies that organisations performing R&D at the interplay between different groups of sectors holding broker positions (Burt 1992). These organisations are aware of R&D developments in these adjacent sectors. Thus, their R&D strategy and collaboration portfolio is characterised by intensive R&D partnerships with organisations of these sectors. In contrast, organisations operating in the adjacent sectors connect via joint R&D to organisations holding "broker" positions. They integrate and generate knowledge based upon developments in other sectors to which they are not directly connected. By and large, we find the same education-related sectors obtaining high scores in betweenness centrality that also ranked highest in degree centrality: *Universities social sciences*, *Miscellaneous education*, *University natural sciences*.

[17] Nodes' size is proportional to the amount of collaborative R&D subsidies acquired by a sector's organisations and the links' widths to the level of the sectors' non-random dyadic resource complementarity. Visualised relations are limited to those with above average complementarity values. Sectors that do not show any above average complementarity relation to any other sector are not shown.

When looking at the betweenness centrality of non-education related sectors, *N&E research* takes a central position as it operates at the interplay of *Electronics* and *Universities Nat*, both with relatively high betweenness centrality scores as well. Accordingly, this sector is particularly important in connecting the education and non-education sphere. The same applies to *Public administration* that also unsurprisingly obtains a high betweenness centrality. There are, however, also some unexpected results with respect to betweenness centrality. For example, the social work sector (*Social work*) turns out to be an important link between service sectors (*Residential*, *Accommodation*, *Human resources*). Similar results hold for associations (*Associations*), which link different educational sectors and additionally connect these to the print (*Print*), arts (*Art*), and unions as well as other membership organisation (*Membership organisations*) sectors.

While the position of sectors in Figure 4-4 should not be over-interpreted, as they are by and large chosen to maximise visual clarity, the figure nevertheless suggests a division of the complementarity space into two parts. The first primarily represents the education sectors (upper left half) and the second includes the majority of the other sectors (lower right half). While there are notable exceptions of sectors bridging this division, e.g., *Research natural sciences & engineering (N&E)*, *Telecommunication*, *University* (representing all subsidised projects for general support of university activities), *University natural sciences*, and *University engineering*, it still seems to be the case that in general collaboration intensities are larger within the two (education & non-education) spheres than between the two.

4.4.2.2 A view on dyadic complementarity

The complementarity space also gives insights into dyadic complementarity patterns. The top-ten relations are presented in Table A4-5 in the Appendix. High values indicate relatively high knowledge integration potentials and should thus be a regular part of organisations' alliance portfolios. For the complementarity space in 2010, we observe the strongest complementarity relation to exist between *Applied university sport* and *University sport*, which does not appear to represent resource complementarity in a strict sense, as the distinction is rather organisational (university of applied science and university) than cognitive or technological. However, in many instances, universities of applied science and universities offer different types of expertise. In general, universities are more frequently focused on the theoretical side, while universities of applied science typically concentrate on practical issues within the same field. While differentiating between the two types of organisations is important in the majority of instances, in this case, both academic organisations are likely to rely on similar knowledge, implying that the relation is rather characterised by science similarity than complementarity. The fifth strongest relationship exists between *Social security* and *Air transport* and needs some explanation as well, as it appears somewhat surprising. Its high value is caused by the few inter-sectoral collaborative projects in which both sectors are generally participating, which applies a strong weight to the single collaborative project organisations of both sectors. The project's objective is the development of concepts for preventative health and safety measures in the air transport sector. The German Statutory Accident Insurance (*Deutsche Gesetzliche Unfallversicherung*) and the Fraport AG participate in the project, strengthening the relation between the two sectors. Hence, this relationship is very reasonable given the reliance of the transport sector on manual labour required at inconvenient working hours.

This example nicely underlines the advantage of the data at hand, which is not restricted to typical manufacturing related R&D but allows for identifying complementarity with and among none-manufacturing related sectors as well.

Rank	Degree centrality 1990	Degree centrality 1995	Degree centrality 2000	Degree centrality 2005	Degree centrality 2010
1	Associations	Research natural sciences & engineering (N&E)	Programming	University economics	University social sciences
2	University natural sciences	University natural sciences	Legal	University social sciences	Miscellaneous education
3	Ground transport	Wood	University economics	Membership organisations	Research natural sciences & engineering (N&E)
4	Food	Programming	University hospitals	Public administration	Research social sciences & humanities (S&H)
5	University engineering	University medical	Miscellaneous education	Research natural sciences & engineering (N&E)	University natural sciences
6	Research social sciences & humanities	Ground transport	ICT services	Programming	Public administration
7	Whole sale	Food	Research natural sciences & engineering (N&E)	University natural sciences	University economics
8	University economics	University economics	University social sciences	Applied university miscellaneous	Associations
9	Air transport	Engineering & architecture	Health & hospitals	ICT services	Social work
10	Print	University engineering	Whole sale	Legal	Machine engineering

Table 4-1. Top-10 ranks in degree centrality.

Other notable relations are less surprising. For instance, *Security* and *Residential*, *Coal* and *Oil*, and *University natural sciences* and *Research natural sciences & engineering* are strongly complementary. In addition, *University hospitals* appear frequently in this list offering complementary resources for medical faculties (*University medical*).

4.4.3 Dynamics of sectors' knowledge integration potential

Above we noted that complementarity is inherently dynamic and that it has to be analysed over longer time to identify changes in attractiveness of sectors' knowledge for other sectors. We exemplify this dynamics by the rise of the telecommunication and ICT related sectors over time. Figure 4-5 gives an answer to whether we can observe such development in the complementarity space.

Rank	Betweenness centrality 1990	Betweenness centrality 1995	Betweenness centrality 2000	Betweenness centrality 2005	Betweenness centrality 2010
1	University natural sciences	University natural sciences	Electronics	University social sciences	University social sciences
2	University engineering	Research natural sciences & engineering (N&E)	Legal	Research natural sciences & engineering (N&E)	Miscellaneous education
3	Ground transport	Public administration	Programming	Membership Organisations	Public administration
4	Research natural sciences & engineering (N&E)	Electronics	Research natural sciences & engineering (N&E)	Secondary education	Social work
5	Associations	Engineering & architecture	University natural sciences	University economics	University natural sciences
6	Public administration	Programming	Food	University natural sciences	Research natural sciences & engineering (N&E)
7	Electrics	Ground transport	University hospitals	University architecture	Ground transport
8	Electronics	Wood	Whole sale	Applied university social sciences	University hospitals
9	Metal processing	Food	Health / hospitals	Finance	Secondary education
10	Warehouse	Energy	Remediation	Wood	Health / Hospitals

Table 4-2. Top-10 ranks in betweenness centrality.

The two plots show the ranking of the three sectors representing the ICT industry (*ICT services*, *Programming*, and *Telecommunication*) with respect to degree and betweenness centrality in the complementarity space. The lines for *ICT services* and *Telecommunication* behave according to our hypotheses. They start from very low ranks in the beginning of the nineteen-nineties and quickly gain in both centralities until the late nineties. From the year 1997 onward, however, both sectors show a somewhat distinct development path, with the centrality (in particular, betweenness) of *Telecommunication* dropping strongly before stabilising somewhere in middle ranks. *ICT services* continue rising and after 1999 remain within the top-ten sectors in degree centrality. The sector, however, also drops in betweenness to middle ranks. In contrast to these two sectors, *Programming* keeps its high rank (above top-thirty) in degree centrality throughout the observational period while it simultaneously decreases in betweenness centrality before starting to rise again after 2009. The latest rise might be due to the renewed interest in programming services because of the mobile application development.

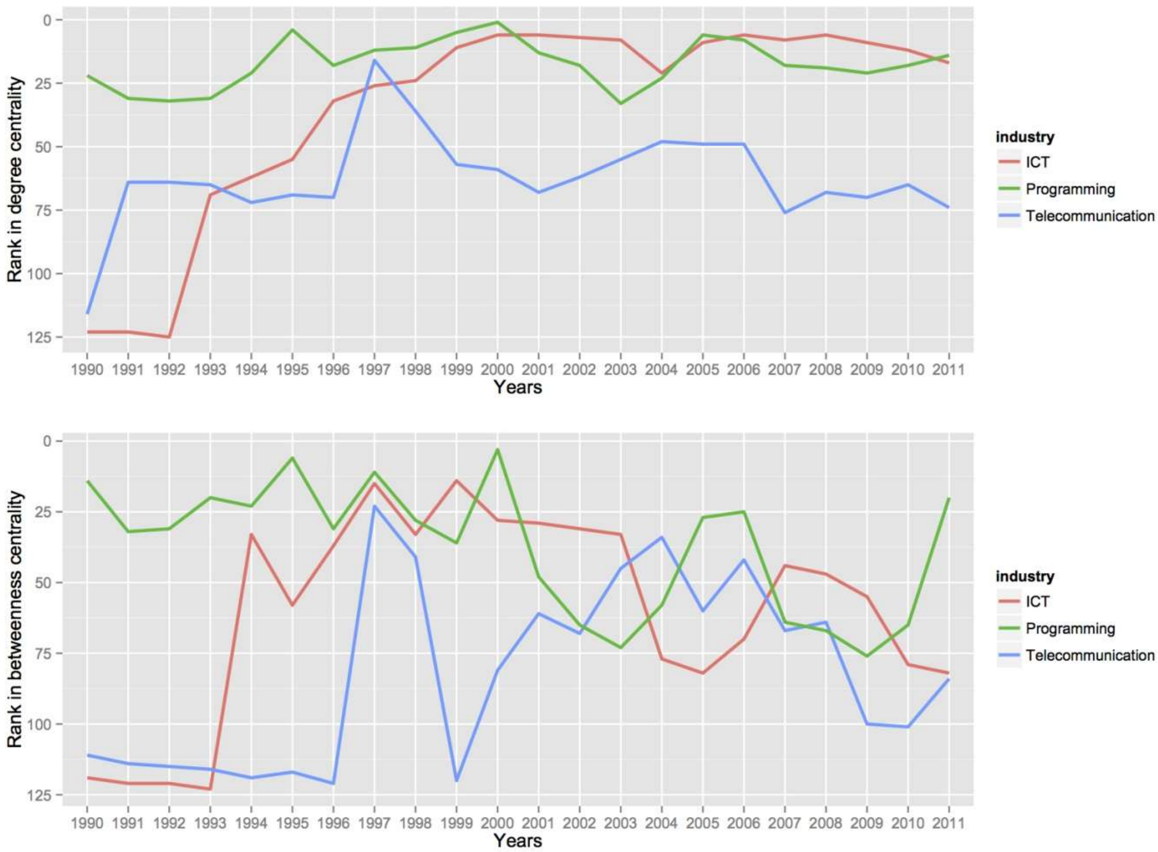


Figure 4-5. Centrality of ICT related sectors.

Hence, the developments of *ICT services*' and *Telecommunication*'s centralities in the complementarity space support the dynamic notion of complementarity and indicate an increasing relevance of these sectors over time, whereby they confirm hypothesis 1. The effects of this economic and technological development are particularly visible for degree centrality in the early nineteen-nineties where these two sectors gain massively in centrality. Their continuously high degree centrality measures that are contrasted by decreasing betweenness centrality suggest that these sectors gain a strong complementarity position within a relatively large group of sectors, while at the same time becoming less relevant in the global complementarity space.

4.4.4 Clustering, fragmentation, and rich-club

Figure 4-6 and Table A4-2 in the Appendix give give impressions on the evolution of essential characteristics of the complementarity space. Most notably, we observe that the space grows denser over time. For instance, the number of positive edges, i.e. positive complementarity relations, increases from less than 300 in 1990 to almost 1,100 in 2011. As the number of sectors (nodes) remains the same, it implies that the density of the space increases in this time period from 3 to almost 15 percent (lower plots in Figure 4-6), which parallels an increasing average complementarity (upper plot).

Figure 4-4 also suggests the complementarity space being rather homogenous in structure, as the eye does not catch any clear components or fragments. However, the arrangement of the nodes does not take link weights into account. We therefore rely on the measures of global clustering (Barrat et al. 2004, Opsahl et al. 2008), number of communities, and modularity for weighted networks (Newman & Girvan 2004). Their value developments over time are shown in Figure 4-7. Crucially, we compare these measures to the values that can be expected on a random basis. The grey area in the plots shows the 95 percent interval for these measures' values estimated on the basis of comparable random weighted networks (Opsahl et al. 2008).

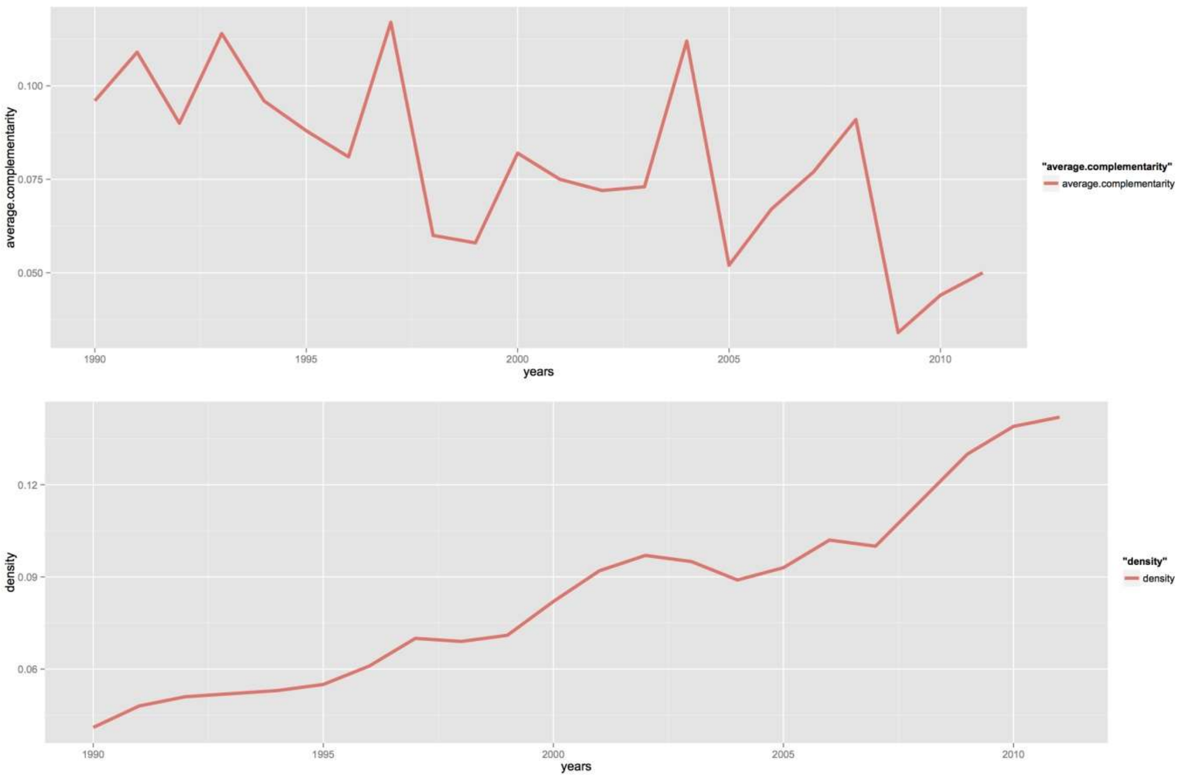


Figure 4-6. Evolution of complementarity space (1).

The plots reveal that the clustering of the network remains well above what can be expected (upper left). Hence, sectors tend to form groups or communities of strong mutual complementarity. An example of such a community of sectors, which is characterised by substantial alternating complementarity relations among its members, is the triangle of *Ground transport*, *Warehouse*, and *Ship transport* visible in the lower middle of Figure 4-4. Each of these sectors holds resources valuable to the other two, which are exploited in mutual collaboration. A portfolio or network perspective on these patterns of complementarity suggests that organisations' R&D activities should be able to reproduce or reflect such complexes or communities.

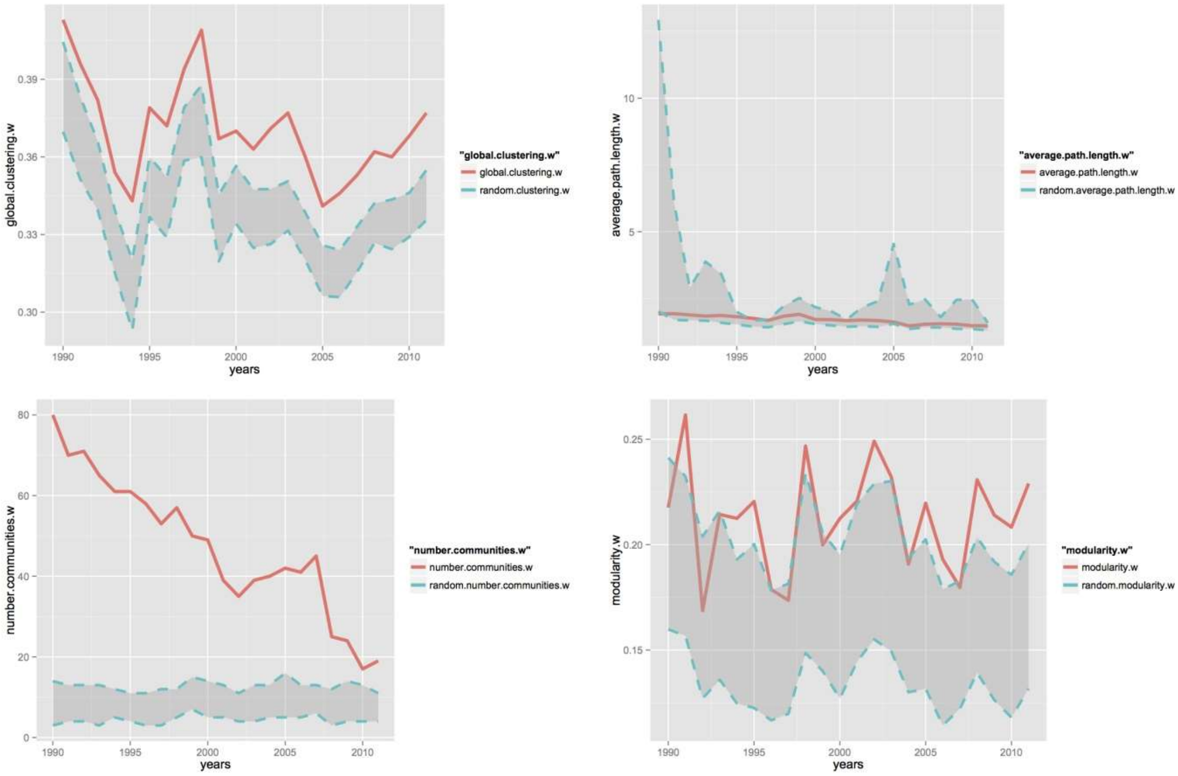


Figure 4-7. Evolution of complementarity space (2).

Although steadily decreasing over time, we observe the same for the number of communities depicted in the lower left plot. The values of the modularity measure (lower right) are larger than the according random values for the majority of years. In the remaining years they are at least close to or directly at the upper bound. Both findings imply that sectors are intensively linked within communities of other sectors but rather weakly connected to sectors belonging to other communities. Hence, the hypothesis 2 of a community-type structure within the complementarity space is confirmed. This structural characteristic is relatively stable over time, whereas the number of communities decreases over time due to the space's increasing density (see Figure 4-7).

4.5 Conclusions

The use of collaborative R&D at the level of organisations is evident and takes place to an increasing extent (Hagedoorn 2002). The basic rationale for this is to benefit from the value creation potential of pooled resources driven by technology complementarity. The structure and dynamics of inter-sector technological complementarity in R&D, however, are largely unknown. This paper allows for first insights into the structure and dynamics of these relations. We used information on the frequency of inter-sector R&D collaboration to approximate technological complementary. On this basis, we estimated sectors' knowledge integration potential in R&D and mapped the resulting complementarity space for 129 sectors in Germany. This space shows sectors being complements both from a dyadic and portfolio/network perspective. This latter is important, as complementarities may only become fully effective when integrated into a complete set of different knowledge resources from multiple sectors. With the identification of the complementarity spaces' community-type structure, our results provide further empirical support for the portfolio approach to resource sourcing in general and the idea of resource completeness in particular.

In addition, we investigated the complementarity space and its dynamics using tools from social network analysis. By these means we explored sectors' complementarity relations and their position within this space from a static as well as from a dynamic perspective. The latter particularly revealed the shifting demands for knowledge resources among sectors at different time periods. These structural dynamics of the complementarity space may provide a conceptual base for the discussion of factors that contribute to the generation of organisation-specific relational rents such as partner scarcity, partner network (in-) completeness, or regional and institutional effects (Dyer and Singh 1998, Breschi et al. 2003, Dyer et al. 2008). Crucially, all these discussions need to take the dynamic character of these relations seriously, as our results highlight the shuffling of sectors' importance in the German R&D landscape over time. A good example in this respect is the ICT service sector, which increased its centrality in the complementarity space within few years.

Several limitations should be noted. First, the results might be subject to some political bias, as the underlying database only includes publicly subsidised R&D collaboration projects. Thus, the accuracy of these findings is limited to the degree and extent subsidised R&D projects reflect actual collaboration patterns. This also concerns the external validity of the results, as the paper exclusively uses information on collaboration among German organisations. This means that our results do not capture international collaboration and resources. However, this could be integrated to some extent by widening the database to projects published in the EU CORDIS database including information about the participation in collaborative R&D in the several EU Framework Programmes. Second, while NACE provide some insights into the knowledge resources of collaborating firms, they follow the majority principle and only grasp that fact to a certain extent. But most firms are multiproduct firms, implying the results may also be subject to classification error in this context or at least biased by some unidentified similarity in technological knowledge complementing major products. Linking the organisation-level network data presented here to other data sets might, therefore, offer rich avenues for further improve of this line of research. Third, collaborative R&D only partially captures technological complementarity. There do exist multiple additional ways of knowledge integration and interactive learning. Future research should examine the relationship between technology complementarity in R&D and patterns of for example inter-sectoral labour mobility (Neffke and Henning 2013) or product embodied knowledge spillovers (Boschma and Iammarino 2009). Fourth, this paper has presented only a measure of technology complementarity. Complementarity is, however, only one dimension of knowledge relatedness, which also includes a similarity dimension as well as the interaction of similarity with complementarity. Lastly, a more clear-cut and explicit classification of knowledge into scientific and technological knowledge (see Makri et al. 2010) might improve understanding the role of the education and academic sector in our analysis.

In addition to these shortcomings, some further issues need to be pointed out. Most importantly, there is a difference between the knowledge integration potential of complementary resources and the value, which will actually be realised by the collaborating organisations (Madhok and Tallmann 1998). The knowledge integration potential in R&D

relates to the implementation of collaborative R&D efforts. The actually realised value by contrast, involves the proper combination of trust, commitment, resource exploitation, and smart alliance management (Lambe and Spekman 1997, Dyer and Singh 1998, Ireland et al. 2002, Shah and Swaminathan 2008, Wassmer and Dussauge 2011). Hence, the realised value of collaborative R&D is a function of the potential value for which the complementarity space may provide an (first) efficient guiding. However, there are many more elements in this function. Accordingly, the dyadic and portfolio perspective of the complementarity space may be interpreted as an upper bound of two sector's value creation potential based on joint collaborative R&D efforts. The future research agenda will, therefore, have to include the identification of the effects of technology complementarity on innovation quantity, quality, and novelty both at the micro-level of organisations as well as from a more aggregated (sectoral and spatial) system perspective (see also Makri et al. 2010 for these propositions and Castaldi et al. 2015 for a first empirical approach). Especially at the spatial system level, this could help to shed more light on relationship between spatial proximity and access to complementarity resources in interactive learning, as recently discussed by D'Este et al. (2013).

Appendix A4

Short name	NACE	Short name	NACE	Short name	NACE	Short name	NACE
Agriculture	A1	Miscellaneous manufacturing	C32	Research natural sciences & engineering (N&E)	M721	Applied university engineering	855a
Forest	A2	Machine repair	C33	Research in social sciences & humanities (S&H)	M722	Applied university administration	855b
Fish	A3	Energy	D35	Advertising	M730	Applied university architecture	855c
Coal	B5	Water supply	E36	Private research	M733	Applied university natural sciences	855d
Oil	B6	Sewage	E37	Professional activities	M74	Applied university arts	855e
Ore	B7	Refuse	E38	Veterinary	M75	Applied university economics	855f
Mine	B8	Remediation	E39	Rental	N77	Applied university social sciences	855g
Services mining	B9	Superstructure	F41	Human resource	N78	Applied university medical	855h
Food	C10	Excavation	F42	Travel	N79	Applied university miscellaneous	855i
Drink	C11	Miscellaneous construction	F43	Security	N80	Applied university law	855j
Tobacco	C12	Care trade	G45	Cleaning	N81	Applied university psychology	855k
Textiles	C13	Whole sale	G46	Office administration	N82	Applied university Sport	855l
Wearing Apparel	C14	Retail	G47	Public administration	O841	Miscellaneous colleges	P856
Leather	C15	Ground transport	H49	Public service	O842	Miscellaneous colleges arts	856e
Wood	C16	Ship transport	H50	Social security	O843	Miscellaneous colleges economics	856f
Paper	C17	Air transport	H51	Pre-primary education	P851	Miscellaneous colleges social sciences	856g
Print	C18	Warehouse	H52	Primary education	P852	Miscellaneous education	P859
Petroleum	C19	Postal activities	H53	Secondary education	P853	Univ. Hospitals	Q860
Chemicals	C20	Accommodation	I55	Secondary education in engineering	853a	Health & Hospitals	Q861
Pharmaceuticals	C21	Gastronomy	I56	University	P854	Residential	Q87
Rubber	C22	Publishing	J58	University engineering	854a	Social work	Q88
Glass	C23	Motion picture	J59	University administration	854b	Arts	R90
Metal processing	C24	Broadcast	J60	University architecture	854c	Libraries, archives	R91
Metal	C25	Telecommunication	J61	University natural sciences	854d	Amusement	R93
Electronics	C26	Programming	J62	University arts	854e	Associations	S941
Electrics	C27	ICT services	J63	University economics	854f	Unions	S942
Machine engineering	C28	Finance	K64	University social sciences	854g	Membership Organisations	S943
Car manufacturing	C29	Insurance	K65	University miscellaneous	854i	ICT repair	S95
Ships	C301	Auxiliary finance	K66	University law	854j	Miscellaneous services	S96
Trains	C302	Real estate	L68	University psychology	854k	Household	T97
Airplanes	C303	Legal	M69	University sport	854l	Extraterritorial	U99
Vehicle miscellaneous	C309	Management	M70	University medical	854h		
Furniture	C31	Engineering & architecture	M71	Applied university	P855		

Appendix A4-1. Considered industries.

	1990	1995	2000	2005	2010
Nodes	129	129	129	129	129
Edges	338	451	679	764	1151
Density	0.041	0.055	0.082	0.093	0.139

Appendix A4-2. Descriptives of complementarity space.

Year	Rank-correlation between number of subsidised R&D projects and degree centrality	Rank-correlation between number of subsidised R&D projects and betweenness centrality	Rank-correlation dyadically summed R&D projects and complementarity value
1990	0.58***	0.70***	0.26***
1991	0.54***	0.58***	0.26***
1992	0.55***	0.51***	0.27***
1993	0.61***	0.61***	0.28***
1994	0.55***	0.52***	0.28***
1995	0.53***	0.48***	0.28***
1996	0.57***	0.50***	0.29***
1997	0.71***	0.53***	0.29***
1998	0.54***	0.51***	0.28***
1999	0.58***	0.54***	0.29***
2000	0.68***	0.59***	0.30***
2001	0.63***	0.45***	0.31***
2002	0.63***	0.43***	0.31***
2003	0.59***	0.39***	0.30***
2004	0.60***	0.42***	0.30***
2005	0.57***	0.36***	0.29***
2006	0.63***	0.38***	0.31***
2007	0.65***	0.38***	0.30***
2008	0.71***	0.49***	0.30***
2009	0.71***	0.45***	0.31***
2010	0.77***	0.52***	0.32***
2011	0.77***	0.51***	0.31***

Appendix A4-3. Reliability of indices.

Year	Degree centrality Pearson correlation	Degree centrality Spearman correlation	Betweenness centrality Pearson correlation	Betweenness centrality Spearman correlation	Mantel test based on Spearman correlation
1990	0.86***	0.87***	0.81***	0.76***	0.72***
1991	0.95***	0.95***	0.69***	0.69***	0.83***
1992	0.96***	0.95***	0.71***	0.74***	0.75***
1993	0.92***	0.95***	0.75***	0.76***	0.70***
1994	0.93***	0.93***	0.65***	0.77***	0.76***
1995	0.96***	0.96***	0.37***	0.73***	0.80***
1996	0.90***	0.91***	0.76***	0.72***	0.74***
1997	0.90***	0.91***	0.61***	0.65***	0.79***
1998	0.92***	0.92***	0.48***	0.70***	0.77***
1999	0.88***	0.88***	0.42***	0.65***	0.73***
2000	0.85***	0.85***	0.47***	0.58***	0.72***
2001	0.97***	0.96***	0.67***	0.71***	0.88***
2002	0.92***	0.92***	0.56***	0.63***	0.85***
2003	0.90***	0.90***	0.54***	0.63***	0.75***
2004	0.91***	0.90***	0.54***	0.62***	0.73***
2005	0.96***	0.96***	0.48***	0.73***	0.80***
2006	0.92***	0.91***	0.61***	0.74***	0.81***
2007	0.93***	0.91***	0.67***	0.68***	0.75***
2008	0.90***	0.87***	0.47***	0.65***	0.77***
2009	0.97***	0.96***	0.71***	0.66***	0.81***
2010	0.98***	0.97***	0.50***	0.63***	0.84***
1990:2000	0.59***	0.59***	0.57***	0.54***	0.26**
2000:2010	0.73***	0.70***	0.38***	0.41***	0.32**
1990:2010	0.50***	0.50***	0.41***	0.45***	0.21**

Year-by-year correlation of the centrality values and Mantel test from 1990-2010

Appendix A4-4. The inter-temporal stability of the complementarity space.

	Sector 1	Sector 2	Weight	Sector 1	Sector 2	Weight
	1990			1995		
1	Wood	Membership Organisations	1	Unions	Office Admin	1
2	Clothes	Secondary Edu	0.96	Ground transport	Warehouse	0.80
3	Ground transport	Trains	0.55	Whole sale	University Misc	0.79
4	University Eng	Rubber	0.53	University Med	Uni Hospitals	0.68
5	Unions	Associations	0.42	Clothes	Textiles	0.56
6	Energy	Appl University Eng	0.41	University Med	Health & Hospitals	0.47
7	Oil	Public Admin	0.35	Drink	Food	0.46
8	University	N&E Research	0.35	Agric	Misc Construct	0.43
9	Ships	Engineering & architecture	0.32	Uni Hospitals	Health & Hospitals	0.42
10	Air transport	Print	0.30	University Psy	Ground transport	0.39
	Sector 1	**Sector 2**	**Weight**	**Sector 1**	**Sector 2**	**Weight**
	2000			2005		
1	Forest	Petroleum	1	Residential	Appl University Misc	1
2	University Med	Uni Hospitals	0.83	University Med	Uni Hospitals	0.40
3	Human Resource	Broadcast	0.58	Finance	University Arch	0.35
4	Drink	Food	0.54	Gastronomy	Advertising	0.32
5	University Nat	N&E Research	0.47	Finance	Secondary Edu	0.30
6	Accommodation	Insurance	0.46	Ground transport	Warehouse	0.26
7	Clothes	Textiles	0.45	Clothes	Textiles	0.26
8	Appl University Misc	Appl University Adm	0.44	Drink	Food	0.25
9	Superstructure	Excavation	0.44	Misc. Edu	Associations	0.25
10	Remediation	Whole sale	0.42	University Psy	Misc. Colleges	0.25
	Sector 1	**Sector 2**	**Weight**			
	2010					
1	Appl University Sport	University Sport	1			
2	University Med	Uni Hospitals	0.55			
3	Security	Residential	0.53			
4	Coal	Oil	0.41			
5	Air transport	Social Security	0.36			
6	Misc. Edu	Secondary Edu	0.32			
7	University Nat	N&E Research	0.31			
8	Secondary Edu	Associations	0.27			
9	University Psy	University Soc	0.26			
10	S&H Research	University Soc	0.26			

Appendix A4-5. Top-10 complementarity relations.

Chapter 5

Joint R&D subsidies, related variety, and regional innovation

5.1 Introduction

The systemic view on innovation emphasises that innovation is a result of the division and interaction of innovate labour and their embeddedness into knowledge networks (Lundvall 1992). The relevance of such interactions and networks is evident and increasing (Hagedoorn 2002). These insights have been taken up by policy seeking to facilitate innovation activities. While in the past policy focused on stimulating firm-internal R&D processes, today, R&D policies more and more support knowledge sharing and the creation of knowledge networks (Muldur et al. 2006). Amongst the most common tools to achieve these goals are subsidies for joint R&D projects. In such joint R&D projects consortia of organisations share the subsidisation grant and realise the project in a collaborative manner. For example in Germany, about 30% of today's R&D subsidies are given to (collaborative) joint R&D projects (Broekel and Graf 2012).

This shift has severe implications for the scientific analysis of R&D subsidies, which have so far not received sufficient attention (but see Czarnitzky and Fier 2003, Fornahl et al. 2011, Broekel 2013). First, this concerns the fact that effects of subsidies are no longer restricted to individual organisations and hence may be missed in firm-level studies. Second, by subsidising collaborative R&D, innovation policy does not only impact the embeddedness of firms into territorial innovation systems, it may also alter the mode of operation of such systems. The aim of the paper is to contribute to this discussion by picking up the insights from research on territorial innovation systems and translate them to the context of public subsidies for R&D projects. This particularly concerns the importance of access to knowledge from within and outside regional borders (Maskell and Malmberg 2002, Audretsch and Feldmann 2004, Bathelt et al. 2004), the type of knowledge resources shared in research collaboration (Nooteboom 2000, Branstetter and Sakakibara 2002, Breschi et al. 2003) and the embeddedness of regional organisations into inter-organisational knowledge networks (Powell et al. 1999, Fornahl et al. 2011).

The arguments are tested by means of an empirical study on the determinants of regions' innovation growth with a particular focus on subsidies for joint R&D. The study utilises a dataset for 150 German labour markets regions and twenty-one manufacturing industries covering the periods 1999-2003 and 2004-2008. To address endogeneity and spatial as well as relational dependencies, a Heckit two-stage procedure in combination with spatial regression techniques is employed. The results confirm the importance of collaboration initiated or facilitated by subsidies for joint R&D projects for regions' ability to increase innovation output. The effectiveness of policy measures however crucially depends on whether subsidised projects bring together organisations with similar but not too similar (i.e. related) knowledge bases. Moreover, being central in inter-regional networks of subsidised R&D collaboration stimulates regions' innovation growth.

The paper is structured as follows. The subsequent section presents theoretical insights and empirical evidence on the role of (collaborative) R&D subsidies at the firm and region level.

The description of the empirical data is content of section three. Section four explicates the empirical approach and the models used to analyse determinants regions' innovation growth. The presentation and discussion of the results are subject of the forth section. Section six summarises and concludes the paper.

5.2 Innovation policy, collaborative R&D subsidies and innovative outcomes

Innovation is undoubtedly the driver of persistent (regional) competitive advantage and development. However, social returns to innovation and R&D investments exceed private returns, which may lead to an underinvestment in R&D from a societal perspective (Arrow 1962). The positive externalities associated with the generation of innovation give the prime justification for public support to private R&D activities. While policy employs a wide range of tools in this context, R&D subsidies to private R&D projects are among the most important and most frequently used (Aschhoff 2008). Empirical literature on R&D subsidies so far concentrates on the allocation and the effects of R&D subsidies at the firm-level. Common findings concerning the allocation of R&D subsidies are a higher likelihood of subsidisation being positively related to the number of business units, collaboration with universities, previous experiences and high R&D intensity (Busom 2000, Blanes and Busom 2004). Regarding the effects of R&D subsidies, the literature shows that they positively impact firms' patenting, innovation efficiency, employment growth, and R&D efforts (Czarnitzki and Fier 2003, Czarnitzki and Hussinger 2004, Czarnitzki et al. 2007, Koski 2008, Zúñiga-Vicente et al. 2014).

However, the way R&D subsidisation programs are designed has been subject to significant changes. R&D subsidies were traditionally awarded to projects conducted by an individual organisation. This organisation was in charge and solely responsible for completing the project. Since the middle of the nineteen eighties this way of allocating R&D subsidies was extended by the subsidisation of joint R&D projects. In this case, R&D subsidies are granted to research consortia that realise R&D projects in a collaborative fashion. Moreover, they have to grant each other access to knowledge, R&D resources, and intellectual property related to the project (for a more extensive discussion see Broekel and Graf 2012).

The shift in the design of R&D subsidisation policies reflects the increasing emphasis on territorial and sectoral innovation systems in the scientific literature (Lundvall 1992, Breschi and Malerba 1997, Cooke et al. 1997). The systems view on innovation highlights that firms do not innovate in isolation but extensively rely on collaboration and interactions with firm-external actors. Accordingly, Broekel (2015) argues that by subsidising joint R&D projects, policy does not only influence organisations' internal R&D process but also collaboration and interaction activities. For instance, by providing monetary incentives to collaborate, organisations are more likely to engage into collaborative activities in general and thereby increase their interdependence with external actors. This is however not uniform over all types of organisations, technologies, and industries. R&D subsidies are used by policy to support areas, which it perceives to be of special importance. In Germany, this particularly applies to new technologies and so-called key technologies (Fier 2002). Some R&D subsidisation initiatives are also selective in terms of supported collaboration partner combinations. For instance, some programs explicitly seek to strengthen regional collaboration (Koschatzky and Zenker 1999) and some even support only regional collaboration within the boundaries of a particular technological field (Dohse 2000). Another configuration of collaboration that is more likely to be supported than others is when public science organisations partner with firms. Such interactions are perceived to be essential for society-wide knowledge diffusion and exploitation of basic research (Beise and Stahl 1999). Broekel and Graf (2012), moreover show that by participating in subsidised joint R&D projects, organisations are embedded into inter-organisational knowledge networks. These networks emerge either without policy intervention or by organisations participating in multiple subsidised R&D projects and organisations transferring experiences and knowledge between projects. In these cases, organisations' knowledge may diffuse along the direct and indirect relations in the network. The more prominent (central) an organisation's position in such (subsidised or unsubsidised) knowledge network, the more likely it will be exposed to and gain access to innovation-relevant knowledge in the network (Powell et al. 1999, Fornahl et al. 2011).

In summary, subsidies for joint R&D projects may have two distinct impacts that go beyond the boundaries of a single organisation. First, the effects at the organisational level emerging from the subsidies for joint R&D are likely to translate to the more aggregate level of innovation systems, as organisations interact with their local surroundings (Camagni 1991, Oerlemans and Meeus 2005). That is, through manifold intended and unintended interactions, effects of R&D subsidies granted to one organisation are likely to be transmitted to other organisations part of the same territorial innovation system.[18] Second, Broekel (2015) argues that subsidies for joint R&D additionally influence the embeddedness of organisations into such systems and thereby impact its entire working and set-up, since subsidised R&D collaboration are one way of how organisations interact with the innovation systems. In addition, the availability of subsidised R&D collaboration alters the attraction of other modes of interaction (e.g. unsubsidised collaboration).

The extent and significance of the two effects thereby depends on a number of factors. Amongst these is the magnitude of changes at the organisational level. That is, the impact of subsidies at the organisational level has to be significant in relation to an organisation's activities. The organisation also needs to be strongly embedded into the system. Therein, the importance of organisations for the functioning of territorial innovation systems varies considerably (Ter Wal and Boschma 2007). It seems plausible that in particular gatekeeper organisations, which keep regional networks integrated and maintain connections to inter-regional networks, are crucial in this context (Morrison 2008). If these significantly change their behaviour according to R&D subsidisation, this change is most probable to feedback into the entire system. For instance, R&D subsidisation may allow these organisations to tap into new knowledge bases that were too expensive to connect to prior subsidisation.

The paper seeks to add to this literature by studying what regions gain from their organisations' participation in subsidised R&D in general and in subsidised joint R&D in particular. With respect to the latter, in the foreground are especially implications of collaboration partner choice in terms of (1) their geographic location, (2) their knowledge resources, and (3) their importance in inter-regional knowledge networks.

[18] Similar can be argued for sectoral innovation systems, these are however beyond the scope of the present paper.

Concerning the first, we can expect a strengthening of the territorial innovation system when R&D subsidies bring together regional organisations and initiate regional collective learning processes (Isaksen 2001). The benefits of these may include cheaper and more frequent face-to-face communication, as well as easier establishment of trust (Williamson 1999, Storper and Venables 2004). However, there might be instances when regional interactions are already fully developed and further support is unnecessary or even harmful. This particularly concerns regional lock-in situations in which regional organisations are unable to leave a particular development trajectory, which delivers suboptimal economic results (Grabher 1993). Such situations are likely to be characterised by dense regional networks with few outside relations. The stimulation of inter-regional collaboration is more beneficial in this case (Broekel 2012).

Second, the fit of knowledge resources among partners in subsidised R&D collaboration matters. It is empirically shown that R&D collaboration offers maximal value creation potentials when providing access to related (knowledge) resources (Gulati 1998, Das and Teng 2000). Partners with related knowledge are characterised by sufficient potentials to develop novel solutions and at the same time are still able to engage in efficient communication (Nooteboom 2000). Hence, as for unsubsidised collaboration, subsidised R&D collaboration will be particularly beneficial when partners with related knowledge come together (Breschi et al. 2003). Fornahl et al. (2011) provide some evidence for this argument at the firm-level, which we seek to extent to the regional level.

Moreover, knowledge networks play a crucial role for the diffusion and dissemination of knowledge in space (Castells 1996, Boschma and Ter Wal 2007). In order to benefit from knowledge diffusing in these networks, organisations need to hold central positions. Organisations can obtain central positions when linking to other organisations in central positions. Hence, it can be expected that subsidised R&D collaboration is particularly beneficial for regions when it is used to establish links to other central organisations and regions. These claims are tested by an empirical study relating the dynamics in regions' innovation output to their organisations' participation in subsidised R&D, which is presented in the following.

5.3 Data

5.3.1 Data on R&D employees, patents, and regional characteristics

In order to assess the contribution of R&D subsidies to regions' growth in innovation output dynamics, we relate regional knowledge inputs to the changes in innovative output generated by organisations located within a region. We thereby take into account that industries vary considerably in their innovation intensities (Arundel and Kabla 1998), which implies that the industrial structure of regions heavily impacts regions' innovative success. To deal with this, we follow Broekel (2012) and estimate all variables in an industry-specific fashion. To do so, we differentiate between 21 manufacturing related industrial sectors, which are defined on the basis of Schmoch et al. (2003). These sectors are defined such that patent data (organised according to the International Patent Classification) can be matched to industrial employment data, which is organised by the industrial classifications NACE.[19] While Schmoch et al. (2003)

[19] Nomenclature Générale des Activités Économiques dans les Communautés Européennes (NACE).

put forward 44 sectors, some of these are defined on the basis of three-digit NACE codes. Our data at hand only provides information at the two-digit NACE level. For this reason, we aggregate the 44 sectors into 22 sectors that can be assigned to two-digit NACE industries. One of these sectors (Publishing & Printing) does not account for positive patent numbers in any of the labour market regions and is therefore dropped (see Table A1 in the Appendix). We refer to these sectors as industries in the following.

As regional units we chose the 150 German labour market regions as defined by Eckey et al. (2006). The choice of labour market regions as spatial unit of analysis is based on Eckey et al. (1990). They point out that regions defined on behavioural settings generally perform better than administrative units, because the former do reflect economic relations in terms of, for example, commuting flows and reachability. Their demarcation was confirmed to be suitable in various other studies (see e.g. Kosfeld et al. 2006, Broekel 2012). By means of spatial regression techniques we will nevertheless take further spatial dependencies into account.

As usual in this type of literature, innovation output is approximated by patent counts, which are taken from the German Patent and Trademark Office (DPMA) within the period from 1999 to 2008. The inventor principle is applied to regionalise the patent data, i.e. each patent is assigned to the labour market region where its inventor is located. In the event a patent being developed by multiple inventors located in different regions, it is equally assigned to each region.

Accordingly, our empirical observations are industry-regions. The growth of innovations (patents) (gI) in region r and industry i is calculated as the log difference between the levels of $I_{r,i}$ in two time periods t and $t\text{-}1$.

$$(5.1) \qquad gI_{r,i} = log(I_{r,i,t}) - log(I_{r,i,t-1})$$

At the regional level, patent numbers are known to fluctuate strongly between years (Buerger et al. 2012). Moreover, we are particularly interested in the long-term effects of subsidies. Looking at the data for two 5-years periods (1999 to 2003 and 2004 to 2008) addresses both issues. That is, we average the patent numbers for each of the two 5-years periods and calculate the growth rate as log difference between the base period ($t\text{-}1$: 1999-2003) and the subsequent period (t: 2004-2008). The resulting growth rate $gI_{r,I}$ is then related to a range of regional characteristics and subsidisation-based variables presented later.

However, few regions with positive patent numbers exist for some of the industries, which prevent the estimation of meaningful patent growth rates. We also have little reason to expect significant variations between industries in the impact of R&D subsidies on innovation activities. For these reasons, we increase the robustness of the estimation by pooling all industry-specific observations. To account for any potential biases related to the pooling, we introduce six industry dummies, which will capture potential differences between the five industries defined in Broekel (2007) and a miscellaneous industry (see Table A5.1 in the Appendix).

Besides the industry dummies, the first explanatory variable considered is the number of patents ($PATENTS_i$) generated in the base period 1999-2003 by regional organisations of industry i. This variable captures that regions with low levels of patenting in the base period might find it easier to increase their patenting than regions that are already patenting at higher levels.

In addition to the number of patents, we control for effects related to the size of R&D activities located in a region by taking into account the number of R&D employees in industry *i* (*R&D EMP*$_i$). We obtain data on R&D employees from the employment statistics of the Federal Employment Agency of Germany. The employees are classified according to the NACE-classification. By using the concordance of Schmoch et al. (2003), this data is matched to the 21 industries.

Private R&D can benefit from being co-located to public R&D as provided by universities, research institutes, and a like. Universities and technical colleges generate qualified human capital and may act as sources of knowledge spillovers. The likelihood of these spillovers seems to decrease with increasing geographic distance, hence yielding the largest advantages to firms located close by (Beise and Stahl 1999). In order to capture the wide variety of such organisations, we approximate their presence and quality by means of their R&D output (Moed et al. 2004). More precisely, we consider all publications registered in the Web of Science. The variable *PUBLICATIONS* is the sum of publications weighted by the number of authors located in a particular region in the period 1999-2003.

It is also widely accepted that firms' innovation output is impacted by agglomeration externalities (Beaudry and Schiffauerova 2009). These include urbanisation advantages such as a higher utilisation of public infrastructure, a richer labour market, and smaller distances to suppliers and customers. In a common fashion urbanisation externalities are approximated by population density (*POP_DEN*). The data is obtained from the German Federal Office for Building and Regional Planning. Another form of externalities arises from regional specialisation into certain industries. To approximate such type of agglomeration externalities, we calculate the Herfindahl index on the basis of two-digit NACE manufacturing industries' R&D employment data (*HERFINDAHL)*. This index is considered in squares as well.

Lastly, a dummy variable *EAST* indicates the location of a region in East Germany. East German regions (still) tend to be characterised by lower innovation performance (Broekel et al. 2013). Moreover, regions in East Germany might benefit from a number of public programs being especially designed to decrease the innovation performance gap between the two parts of Germany.

5.3.2 Information on R&D subsidies and empirical variables

Comprehensive information on projects subsidised by the federal government is published in the so-called subsidies database ("*Förderkatalog*").[20] The subsidies database lists detailed information on projects supported by federal ministries between 1960 and 2012. We estimate all figures on the basis of the base period (years 1999 to 2003) in which 16,114 projects split into 27,428 individual funds were granted to 8,489 German organisations.[21] For the definition of variables we utilise information concerning projects' starting and ending data, the magnitude of the granted fund, NACE industry class for each subsidised organisation, and the

[20] http://foerderportal.bund.de/foekat/jsp/StartAction.do.

[21] We follow Broekel and Graf (2012) in defining an organisation as a unique combination of the name of the receiving organisation and the location of the actual executing unit.

collaborative nature of the project. Moreover, all funds are classified according to an internal hierarchical classification scheme developed by the German Federal Ministry of Education and Research (BMBF) called "*Leistungsplansystematik*". The 16 main areas are disaggregated into a varying numbers of sub-classes.

The available industrial classification (NACE) of project participants allows for differentiating between two-digit NACE industries. Subsidised projects can be either individual or joint projects. Joint projects are granted to consortia of organisations ("*Verbundprojekte*") realising a particular research projects. Individual projects are conducted by a single organisation. Participants in joint projects agree to a number of regulations that guarantee significant knowledge exchange between the partners. Broekel and Graf (2012) argue therefore that two organisations can be assumed to collaborate and potentially exchange knowledge when participating in the same joint project at the same time.

The first variable created on the basis of the subsidisation data is $SUBS.INDI_i$. It sums the number of individual projects granted to regional organisations of industry i. A similar variable is defined on the basis of joint projects representing the number of subsidised joint R&D projects ($SUBS.COLL_i$). We have to use project counts instead of sums of Euros to approximate the extent of inflow of public support to R&D because of the diversity in project sizes, scopes, and financial framework. Moreover, all projects are co-financed by the receiving organisation. The relative magnitude of the co-financing is however unknown and may potentially bias the results. The studies by Fornahl et al. (2011) and Broekel (2015) support this decision, as they find effects on innovation activities being related to project counts rather than to the sum of project grants.

On the basis of information on subsidised joint R&D projects, we create an inter-organisational R&D collaboration network. For this, we extract all subsidised joint R&D projects in which at least one organisation of the focal industry i is participating. Hence, the industry-specific networks are not restricted to organisations of the focal industry. To the contrary, in most instances they include considerable numbers of organisations belonging to other industries. Such corresponds to a broad definition of an industry network, as it includes its organisations' knowledge sources (universities, research institutes, firms in other industries). Alternatively, one might define a network exclusively on relations between organisations belonging to one industry. However, such a network does not allow for identifying the role collaborative R&D subsidies play for accessing and exploiting external knowledge since it represents only a small fraction of organisations' knowledge sources. The network's nodes are subsidised organisations and link weights are the count of two organisations' joint appearance in (potentially multiple) subsidised joint R&D projects. The first variable calculated on the basis of this network is the total number of regional collaborations (i.e., links), which organisations in a particular region and industry realised in the period 1999-2003. It is denoted as $REG.COLL_i$. In an identical manner we define *INTER.COLL* as the total number of inter-regional collaboration.

5.3.3 Similarity and related variety

We pointed out above that the potential benefits of collaboration depend strongly on the similarity and relatedness of the collaborating organisations' R&D resources. To approximate the degree of relatedness between two organisations we rely on their industrial classification and establish an index of inter-industrial technological similarity. The measure S_{ij}, which indicates the degree of similarity between industry *i* and *j*, is estimated on the basis of information on individual R&D subsidisation grants, i.e. only subsidised projects executed by a single organisation are considered. The basic idea behind the measure is that most R&D subsidisation programs have a clear technological focus, which is represented in the subsidies data' technological classification scheme ("*Leistungsplansystematik*"). It can then be argued that two industries' R&D resources are similar the more frequently their organisations are subsidised through the same R&D subsidisation scheme. That is, the more frequently they obtain (individual) grants classified into the same technological class. Since the frequency of co-occurrences of industries within the same technological class will increase with the number of grants acquired by their organisations, we resemble the measure of Teece et al. (1994) and Bryce and Winter (2009). That is, we count the number of co-occurrences of grants attributed to two industries' organisations within each of the more than 1,100 6-digit technological classes in the R&D subsidies data. This number is denoted as J_{ij} and represents the number of individual projects granted to organisations of industry *i* and organisations of industry *j* classified into the same 6-digit technological class. J_{ij} will naturally increase with the number of subsidised projects the organisations of the two focal industries acquire. It is therefore adjusted with the number of co-occurrence that can be expected if all industries are randomly assigned to 6-digit technological classes. *K* is the number of technological classes and n_i represents the total number of individual projects organisations of industry *i* are active in. n_j is the corresponding number for industry *j*. The expected number of projects within the same technological class in which industry *i* and *j* are active (x_{ij}) can then be seen as hypergeometric random variable (Bryce and Winter 2009, p. 1575f.):

$$(5.2) \qquad P[X_{ij} = x] = \frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}}$$

Its mean can be estimated as

$$(5.3) \qquad \mu_{ij} = E(X_{ij}) = \frac{n_i n_j}{K}$$

and its variance by

$$(5.4) \qquad \sigma_{ij}^2 = \mu_{ij}\left(1 - \frac{n_i}{K}\right)\left(\frac{K-n_j}{K-1}\right)$$

The difference between J_{ij} and the expected value μ_{ij} is estimated and standardised according to:

$$(5.5) \qquad \tau_{ij} = \frac{J_{ji} \;\; \mu_{ij}}{\sigma_{ij}}$$

τ_{ij} is based on "raw" counts co-occurrences within the same technological class. The resulting index is standardised and divided by the maximum similarity score in the sample. Negative values imply strong dissimilarity and hence their interpretation is the same as in the case of zero values. They are set to zero implying that the final similarity index ranges between 0 and 1 with values close to one indicating maximal resource similarity. For the calculation of similarity in the context of this paper, we estimate the annual similarity index for each year between 1999 and 2003 and average the annual values over all years of the base period.

Equipped with this measure, we weight each inter-organisational link by the bilateral resource similarity of the collaborating organisations' industries. On this basis two variables are built: The average similarity of industry *i*'s regional collaboration ($SIM.REG_i$), and the average similarity of its inter-regional collaboration ($SIM.INTER_i$). Here, inter-regional collaboration are defined as the number of collaboration that regional organisations maintain with organisations located outside their region. Following a standard approach in the literature both values additionally enter the regression equation in squared values to model relatedness (Nooteboom 2000, Frenken et al. 2007). Since related resources are characterised by some technological similarity (some but not too much), a positive impact of related variety is confirmed when the linear term will obtain a positive coefficient and the squared term a negative coefficient.

5.3.4 Embeddedness into cross-regional collaboration networks

To model effects related to organisations' embeddedness into subsidised knowledge networks, we construct industry-specific cross-regional (subsidised) collaboration networks. This is, we are aggregating the previously constructed inter-organisational networks to the regional level by combining all link information of organisations located in the same region.

As a result, the networks' nodes are regions with links between two regions indicating the co-presence of their organisations in at least one joint project in which an organisation of industry *i* is participating. The actual number of joint appearances defines the weight attributed to the link. The prominence of a region in the network and hence the potential of its organisations to benefit from network based knowledge diffusion depends on the global centrality of the region in this network. A common measure of global centrality is betweenness centrality, which represents the frequency of a node (region) being part of the shortest paths between any two nodes (regions) in an industry specific network. Given that the network includes link weights, we employ the weighted betweenness centrality measure put forward by Opsahl et al. (2010) to construct the variable $BETWEENNESS_i$.[22] All empirical variables are summarised in Table 5-1. The descriptive statistics and correlations can be found in Appendices A5-2 and A5-3.

[22] We also estimated a region's degree centrality, which however turned out to be highly correlated to SUBS.COLL and was therefore dropped.

Variable name	Description (all variables are at the level of 149 regions)	Data source
gl_i	Growth of patents in industry i	Patstat
$PATENTS_i$	Number of patents in industry i	Patstat
PUBLICATIONS	Number of publications	Web of science
R&D EMPL$_i$	Number of R&D employees in industry i	German labour market statistics
POP.DEN	Population Density	INKAR (2012)
HERFINDAHL	Herfindahl index of R&D employees based on 2 and 3 digit NACE	German labour market statistics
EAST	Dummy for regions in East Germany	INKAR (2012)
SUBS.COLL$_i$	Total number of subsidised joint R&D projects of industry i	Extended funding database BMBF
SUBS.INDI$_i$	Total number of subsidised individual R&D projects of industry *i*	Extended funding database BMBF
BETWEENNESS$_i$	Betweenness centrality measure based on none-technology specific, inter-regional (LMR), network in industry i	Extended funding database BMBF
REG.COLL$_i$	Number of regional collaboration of industry *i*	Extended funding database BMBF
INTER.COLL	Number of inter-regional collaboration of industry *i*	Extended funding database BMBF
SIM.REG$_i$	Average similarity of regional collaboration of industry i	Extended funding database BMBF
SIM.INTER$_i$	Average similarity of inter-regional collaboration in which regional organisations of industry i are participating	Extended funding database BMBF
INDUSTRY.dummies	Dummy variables for six industries	Definition according to Broekel (2007)

Table 5-1. Overview of empirical variables.

5.4 Empirical approach

5.4.1 Growth of innovative output

We identify the contribution of R&D subsidies to regions' industry-specific innovation growth with the following equation:

$$gI_{r,i} = a + b\boldsymbol{K}_{\boldsymbol{r},\boldsymbol{i}} + c\boldsymbol{S}_{r,i} + u_{r,i} \qquad (5.6)$$

where $gI_{r,i}$ represents the growth of innovative (patent) output in industry *i* and region *r*, $\boldsymbol{K}_{r,i}$ is a matrix of region and industry-specific characteristics that are probable to facilitate innovation growth, $S_{r,i}$ is a matrix of variables based on R&D subsidies, and $u_{r,i}$ is the error term.

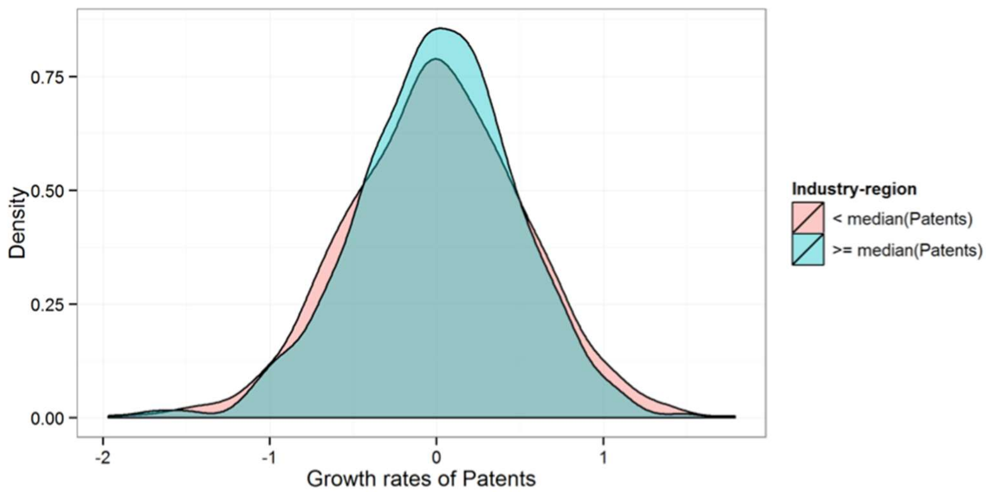


Figure 5-1. Density distribution of unconditional growth rates of patents.

Figure 5-1 shows the density distributions of $gI_{r,i}$ for those industry-regions having either more or less patents than the median.[23] The distributional mass for the industry-regions with less than median patents is more wide spread than that of industry-regions with more than median patents. Simply stated, regions with more patents fluctuate less in their industry-specific patent growth rates than regions with fewer patents. It is regarded as a universal feature in the growth of complex organisations that the variance of the growth rates scales inversely with the levels, usually by a factor that follows a power-law (Stanley et al. 1996, Amaral et al. 2001). We follow Bottazzi et al. (2014) in modelling this variance-scaling relationship directly by introducing a heteroscedasticity term into the stochastic growth process. The identified scaling parameter β is -0.172, which is very close to the parameters reported in the literature on regional employment growth (Duschl and Brenner 2013) or firm growth (Stanley et al. 1996). This parameter is used to rescale the growth rate ($gI_{r,i}$) and thus to clean it from heteroscedasticity.

5.4.2 Endogeneity

We also treat potential endogeneity issues related to the allocation of public R&D funds (Czarnitzki et al. 2007, Aschhoff 2008) by means of econometric model specification, as put

[23] Both distributions are de-meaned to facilitate the comparison of variances.

forward in Hall et al. (2009). Lacking sufficient instrumental variables[24], we employ a two-stage Heckit approach. As the focus of this study is primarily on subsidies for joint projects, we account only for potential endogeneity related to these variables, leaving subsidies for individual projects untreated. Besides the smaller relevance in the paper, it is also the case that noticeably less industry-regions receive individual subsidies, which results in too few observations for a Heckit approach in their case. There are only 344 industry-regions with positive individual subsidised project counts. In contrast, for joint R&D projects this number is as high as 736.

In case of subsidies for joint R&D, we first estimate a probit equation for joint project subsidisation in dependence on regional characteristics explaining their allocation, namely, the number of patents in industry *i* (*PATENTS*), R&D employment in industry *i* (*R&D EMPL*), population density (*POP.DEN*), industry dummies, and a dummy for East Germany (*EAST*). In order to meet the exclusion restriction, we include the number of individual and joint projects in the outcome equation that have been granted to (industry-specific) regional organisations in the years before the base period (between 1990 and 1998). The idea is that the latter variables are clearly exogenous, strongly predictive for future subsidisation, and in contrast to the previously mentioned variables, do not enter the final model predicting regional innovation growth.

The obtained estimates from the two-stage Heckit model subsequently enter the final regression relating innovation growth to regional characteristics and subsidies, as an instrument for the subsidisation of joint R&D. This final regression additionally includes publications (*PUBLICATIONS*) and the Herfindahl index (*HERFINDAHL*), which are likely to impact the effect of R&D subsidies but not their allocation. Moreover, the final regression is constrained to observations with at least one subsidised joint or individual R&D project.

5.4.3 Spatial and relational spillover

It is widely accepted that regions located next to other regions with significant R&D activities benefit from knowledge spillovers (Breschi and Lissoni 2001). The magnitude of these spatial knowledge spillovers decreases with increasing distances between regions (Bode 2004). This may lead to spatially correlated regression errors. We address this is issue in two common ways (Anselin 1988, LeSage 2009). Firstly, we include a spatially lagged variable in the final model accounting for the innovative output of neighbouring regions. For the type of regions studied in the paper, (row standardised) direct neighbourhood relations seem to be most meaningful for creating the according spatial weights matrix. The variable *PATENTS.spatial* represents the sum of a region's neighbouring regions' patent output weighted with these spatial weights. However, despite considering this spatially lagged variable, severe spatial autocorrelation in the error term still remains in a standard OLS model. We therefore apply a spatial simultaneous autoregressive error model (hereafter, spatial error model). Here, spatial dependence is explicitly modelled in the error term:

$$(5.7) \qquad u_{r,i} = \lambda W \quad {}_{r,i} + e_{r,i}$$

[24] We tried a vast range of potential instrumental variables. However, all were suffered from the weak instruments problem.

whereby lambda is the coefficient of the spatially lagged autoregressive errors Wu and W contains the spatial weights representing the structure of the spatial dependence. e are the independent disturbances. Maximum likelihood is employed, as it provides the most efficient estimator for equation 5.7) when the error term is normal distributed.[25]

However, knowledge may not only spill over through space, as it is also shared and transferred within inter-organisational R&D collaboration networks. Accordingly, we also need to control for dependencies potentially arising from regions' network embeddedness and so-called relational spillovers (Maggioni et al. 2007). To do so, we apply the same methodology as in the case of spatial spillovers. That is, we establish a relational weights matrix on the basis of the focal industry's subsidised R&D collaboration network with two regions being relational "neighbours" when being directly linked in the subsidised R&D collaboration network. We then construct a relational lag variable similar to the spatial one. It is denoted as *PATENTS.relational* and represents the sum of a region's relational neighbours' patent output weighted with the (row-standardised) relational weight matrix. In addition, we use the relational weights matrix to test for relational dependencies in the OLS regressions' error terms. Similarly to the spatial dependencies, our results suggest the presence of relational dependencies, which imply that we need to estimate the final model accounting for relational dependencies in the error term. While the spatially and relationally lagged variable can be simultaneously included in one model, we have to specify in the context of dependencies in the error term two final models: one with spatial and one with relational dependencies modelled in the errors.[26]

While we successfully remove spatial dependencies from the error term of the first model (Table 5-3: insignificant Moran's I), we are not able to obtain a model with relationally uncorrelated errors (significant Moran's I statistic in Table 5-3). However, the Moran's correlation coefficient is very low, which indicates significant but uncritical relational dependencies.[27]

5.5 Results

5.5.1 Regional characteristics and innovative growth

Table 5-2 shows the results of the first-stage Heckit estimation with the probability of subsidisation as dependent variable, which is used to generate the instrumentation for the second-stage regression variable *SUBS.COLL*. All variables considered in the estimation gain significance and their positive coefficients meet our expectations. Hence, urban regions (*POP.DEN*) that are doing well in terms of innovations (*PATENTS*) and public (*PUBLICATIONS*) as well as private R&D activities (*R&D EMPL*) are more likely to participate in subsidisation schemes for R&D projects. Moreover, regions in East Germany (*EAST*) are more frequently subsidised than West German regions underlining a certain political motivation to use R&D

[25] The Kolmogorov-Smirnov (KS) test in our model diagnostics (see bottom of Table 5-3) reveals that our assumption is met. Moreover, the spatial error model specification successfully captures the residual spatial autocorrelation, as Moran's I test statistic becomes insignificant. By comparing the models to OLS, both the likelihood ratio (LR) test as well as the Wald test confirms that the captured share of spatial dependence in λ is significant. The spatial version of the Breusch-Pagan (BP) test also fails in identifying the presence of heteroscedasticity.

[26] Of course, the optimal strategy would be to simultaneously model both dependencies in the error term. Such is however not implemented in standard statistical software.

[27] The other model diagnostics are similar to the spatial weight matrix specification.

subsidies to support this part of Germany even twenty-five years after the reunification. *HERFINDAHL* gains a negative significant coefficient indicating that diversified regions are more likely to be subsidised. Past subsidisation (*SUBS.COLL.9098* and *SUBS.INDI.9098*) is also not surprisingly a strong predictor for future subsidisation.

	Probit Selection	**Outcome**
Intercept	-4.630 ***	-77.887 ***
	0.000	0.000
PATENTS	0.304 ***	6.869 ***
	0.000	0.000
PUBLICATIONS		0.510 ***
		0.000
R&D EMPL	0.253 ***	4.462 ***
	0.000	0.000
POP.DEN	0.290 ***	
	0.000	
HERFINDAHL		-9.028 **
		0.0050
EAST	0.685 ***	13.131 ***
	0.000	0.000
SUBS.COLL.9098		0.873 ***
		0.000
SUBS.INDI.9098		0.052 **
		0.007
INDUSTRY.dummies	not reported	not reported
N observations	1671	736
Adj. R-squared		0.8582
Inverse Mills Ratio (p-value)	1.217 (0.332)	
*p-values given below coefficients. Significance symbols: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*		

Table 5-2. First-stage Heckit model.

The results for the final models (using spatial or relational dependencies) are presented in Table 5-3. The first observation is that controlling for spatial or relational dependencies does not impact the coefficients’ significances at all. All significant coefficients remain by and large identical. Hence, we will not differentiate between the two models in the interpretation and just refer to the results of the model using spatial dependencies.

A number of basic regional characteristics gain significance in all models. Most notably, this concerns *PATENTS* and *R&D EMPL* with the first obtaining a negative and the second a positive coefficient. The negative coefficient of *PATENTS* suggests that regions are, on average, able to sustain a high level of patenting only if the local conditions support this level. Given the same local conditions in two regions the region with the lower patent activity will, on average, show the higher growth in patenting, leading to convergence. The positive coefficient of R&D employment suggests that regions with large R&D capacities are more probable to expand in patent output, which is very plausible as well.

The positive coefficient for *PUBLICATIONS* confirms the impact of the quality of the public R&D infrastructure and its potential for knowledge spillovers (Jaffe 1989, Audretsch and Feldman 1996). We also confirm benefits related to regions' specialisation (*HERFINDAHL*). The coefficients of *HERFINDAHL* and $HERFINDAHL^2$ are positive and negative, respectively indicating an inverted u-shape relationship with innovation growth. Low levels of specialisation as well as very high levels reduce innovation growth, while average levels seem to be most beneficial. The finding relates to the presence of Marshall-Arrow-Romer externalities (Glaeser et al. 1992) and supports previous findings in the literature of diversification and specialisation being jointly conducive for innovation (van der Panne and van Beers 2008). In addition, we find a number of industry dummies to be highly significant underlining the heterogeneity of industries with respect to the determinants of regional patent growth.

5.5.2 R&D subsidies and innovative growth

The results obtained from the first model are used to define variable *SUBS.COLL*, which is used in the final model and represents an instrumentation of the expected subsidised joint R&D projects. However the instrumentation on the basis of the Heckit model does not impact our results by and large (see Table 5-3). Most likely, this is due to the numbers of subsidised individual and joint R&D projects remaining insignificant in the final models even when not being instrumented. The observation suggests two things. First, the relation between subsidisation and patent growth at the regional level does not seem to be characterised by strong endogeneity. Second, and this is even more important, the subsidisation of R&D projects does not directly improve regions' capacities to increase their patent output. While, the finding for *SUBS.INDI* confirms the firm-level results of Fornahl et al. (2011), it contrasts the results of Broekel (2015) who identifies a negative impact of these types of subsidies on annual changes in regions' innovation efficiency. The discrepancy suggests that negative effects related to the subsidisation of individual R&D projects are of short-term nature and do not persist in the long run. Potentially, Broekel (2015) picks up a resource enlargement effect. That is, R&D subsidies expand regional R&D resources, which (if not simultaneously compensated by additional output) will lower regions' innovation efficiency.

The insignificance of subsidised joint R&D projects (*SUBS.COLL*) contradicts our expectations of a positive impact, which has also been reported by Broekel (2015). However, the variable gains a positive significant coefficient when the industry dummies are omitted. It might therefore be the case that Broekel (2015) either picks up a short-term effect or that his use of a larger industrial aggregation is responsible for this finding. The latter would imply that industries with higher subsidisation of joint R&D projects are, on average, those industries that show higher growth in patent activities.

Nevertheless, the insignificance of the variables *SUBS.INDI* and *SUBS.COLL* indicates the absence of direct effects on regions' long-term innovation growth that emerges from the subsidisation of R&D projects. The question is therefore why do firm-level studies frequently observe significant relations between R&D subsidisation and firms' innovation output (see e.g. Czarnitzki et al. 2007)? There are two potential explanations. First, the positive effects are restricted to the firm-level and may simply be too small to be identified at the regional level.

Or, second, the existing firm-level studies pick up indirect effects related to the subsidisation of joint R&D projects. These will be discussed in the following.

The first observation on indirect effects is that subsidising joint projects with strong regional participation (*REG.COLL*) might add a bonus to regions' innovation growth. However, we are careful in interpreting this, as the variable is only significant at the 0.1 level. As discussed in the theory section, the potential reason for the relatively low significance is that *REG.COLL* captures all types of subsidised regional collaboration irrespective of the type of partners involved. Moreover, the significance of regional collaboration only becomes visible when considering the degree of similarity of partner resources, whereby *SIM.REG* and *SIM.REG*^{2} remain insignificant. Accordingly, subsidising joint R&D projects play a subordinate role when including intra-regional collaboration, i.e. when multiple organisations from the same region participate in the same joint project. This finding adds to the cue of empirical studies confirming positive effects of regional collaboration (e.g. Arndt and Sternberg 2000). However, our results, as the results of Broekel (2015), might only apply to subsidised R&D collaboration.

Similarly to subsidies for regional R&D collaborations, our results show that supporting inter-regional R&D collaboration generally does not facilitate regions' innovation growth. The coefficient of *INTER.COLL* remains insignificant in all models. However, when controlling for resource similarity a positive significant coefficient is obtained for inter-regional collaboration (*SIM.INTER*). The significance of the positive coefficient is conditional on the inclusion of *SIM.INTER*^{2}, which obtains a negative but insignificant coefficient.[28] While insignificant, it still signals that collaborations with very high similarity values are not beneficial. This meets the idea of related variety. Some resource similarity is necessary to allow for efficient communication and ensure complementary resources (Frenken et al. 2007). However, the higher the degree of partner resource similarity in subsidised R&D collaboration, the more likely are combinations of redundant knowledge resources (Nooteboom 2000). Put differently, similar knowledge resources imply that firms share similar cognition, perceptions, interpretations, and evaluations. The innovative potential for novel resource (re-)combination is therefore reduced in collaborative projects involving similar knowledge resources. While plausible, it still remains unclear why we observe this for inter-regional and not for regional collaboration. Potentially, this is because R&D projects are relatively more costly when partners are located in different regions. As a result, such collaboration particularly hurt organisations when they do not add value, which translates into a negative coefficient of SIM.INTER^2. The missing shared regional context of inter-regional collaboration makes free-riding, moral hazard, and untrustworthy behaviour more likely and attractive (Asheim and Isaksen 2002, Storper and Venables 2004). In other words, as inter-regional collaboration are more prone to yield negative effects in general, partner selection in terms of related resources is even more crucial than in the case of regional collaboration.

[28] By means of testing a linear hypothesis, it can be shown that SIM and SIM^2 are also jointly significant in the Spatial Error Model using either the spatial or relational error matrix.

	Regression with spatial weights		Regression with relational weights	
	Controls	**Full**	**Controls**	**Full**
Intercept	0.169 0.453	0.179 0.4237	0.191 0.3414	0.198 0.3253
PATENTS	-0.215 *** 0.0000	-0.221 *** 0.0000	-0.214 *** 0.0000	-0.203 *** 0.0000
PUBLICATIONS	0.038 *** 0.0000	0.034 *** 0.0000	0.035 *** 0.0000	0.032 *** 0.0002
R&D EMPL	0.007 *** 0.0002	0.007 *** 0.0005	0.007 *** 0.0005	0.006 *** 0.0008
POP.DEN	-0.125 *** 0.0005	-.121 *** 0.0007	-0.129 *** 0.0000	-0.126 ** 0.0000
HERFINDAHL	1.949 * 0.0241	1.950 * 0.0230	2.375 ** 0.0054	2.341 ** 0.0058
HERFINDAHL^2	-4.886 ** 0.0080	-4.762 ** 0.0094	-5.752 ** 0.0017	-5.538 ** 0.0024
EAST	-0.011 0.8641	-0.019 0.7800	-0.005 0.9281	-0.013 0.8060
SUBS.COLL(instrum.)	0.006 0.8333	-0.005 0.8773	0.001 0.9638	-9.13e-4 0.7546
SUBS.INDI	-0.005 0.4136	-0.006 0.3137	-0.005 0.3486	-0.006 0.2827
PATENTS.spatial	5.00e-5 0.4033	4.23e-5 0.4339	6.08e-5 0.2919	5.52e-5 0.3371
PATENTS.relational	1.47e-6 0.5198	6.76e-7 0. 7661	1.60e-5 0.4944	9.13e-7 0. 7546
REG.COLL	0.005 0. 1494	0.006 ‘ 0. 0972	0.005 0. 11451	0.006 ‘ 0. 098
INTER.COLL	-4.60e-5 0. 7037	-1.26e-4 0. 3362	-2.69e-5 0. 8806	-6.57e-5 0. 6124
BETWEENESS		3.81e-4 * 0.0431		3.28e-4 * 0.0471
SIM.REG		-0.004 0.7446		-0.002 0.8308
SIM.INTER		0.082 * 0.0286		0.085 * 0.0240
SIM.REG^2		9.40e-5 0.7071		4.11e-4 0.8652
SIM.INTER^2		-0.008 0.2208		-0.084 0.2059
INDUSTRY.dummies	not reported	not reported	not reported	not reported
AIC	825.25	824.21	823.45	822.92
KS-Test (p-value)	0.2652	0.3341	0.2407	0.4756
BP-Test (p-value)	0.2715	0.3912	0.3115	0.3621
Moran’s I (p-value)	0.6515	0.6385	0.000 ***	0.000 ***
Lambda	0.2917	0.2832	0.1787	0.1688
LR-test (p-value)	0.0272 *	0.0351 *	0.0097 **	0.0166 *
Wald test (p-value)	0.0171 *	0.0205 *	0.0048 **	0.0082 **
VIF	1.750	1.8563	1.750	1.8563
*p-values given below coefficients. Significance symbols: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*				

Table 5-3. Second-stage SEM Model (spatial weights).

In this sense, our findings extend the analysis of Broekel (2015), who tests for collaboration between science organisations and firms. In our definition of similarity, we also include similarity potentially existing between firms in distinct industries and with science organisations. The conclusions are nevertheless similar: The effectiveness of R&D subsidies crucially depends on whether joint projects bring the right partners together. In this case, these are organisations from different regions with related knowledge resources.

BETWEENNESS also obtains a positive significant coefficient in all models. The variable approximates regions' global centrality in the (industry-specific) German (subsidised) R&D collaboration network and reflects the idea of easy access to knowledge diffusing in the network. This finding is remarkable, as it points to the relevance of structural features at the level of the entire industrial knowledge network. Betweenness centrality only partly depends on direct links of a region to other regions. The measure is strongly shaped by the centrality of these adjacent regions in the overall network and on the absence of links (collaboration) between regions to which the focal region is only indirectly linked to. In this sense, our finding suggests that the effects of subsidising joint R&D projects go beyond the establishment of direct relations between organisations and regions. Subsidising joint R&D projects implies that a network of subsidised collaborations is established. Some regions become very central in this network, while other regions are rather peripheral in this network. Our results give evidence for the existence of a *network effect*: Innovation grows, on average, more in the central (betweenness centrality) regions in this network than in other regions. Hence, the network structure generated by subsidising joint R&D projects seems to have a more significant level on the innovation output than the subsidies themselves. This surely deserves more attention in future research.

5.6 Implications

The study shows that collaboration established by organisations participating in subsidised joint R&D impact regions' innovation growth. However, the interpretation of the findings is constrained by the unclear relation between subsidised and unsubsidised R&D collaboration. To be more precise, the *substitution* and *additionality* hypotheses concerning the relation between public R&D subsidies and private R&D efforts may in a refined way also apply to subsidised R&D collaboration.

Substitution hypothesis: It can be argued that subsidised R&D collaboration simply replace collaboration that would have been realised without subsidies anyway. In this case, subsidies for R&D collaboration are subject to a bandwagon effect. If this applies, we can interpret patterns of subsidised R&D collaboration as "*representatives*" of unsubsidised collaboration. In this case, our results suggest that inter-regional collaboration with access to related variety stimulate regional innovation growth. Whether such collaboration are subsidised or not does not matter. The substitution hypothesis is however a very strong one, as the subsidised collaboration need to be absolutely identical to those realised without subsidisation. Hence, we rather believe that the additionality hypothesis is at least partly true.

Additionality hypothesis: The additionality hypothesis suggests that subsidies for collaborative R&D stimulate R&D collaboration that otherwise would not have been realised. According to this line of argument, it can be expected that subsidised R&D collaboration are structurally different from and thereby unrepresentative for unsubsidised R&D collaboration. It implies that our results do not hold for collaboration activities in general, as they are restricted to subsidised collaboration. Accordingly, organisations in regions with strong innovation growth are able to utilise subsidies for joint R&D projects to get access to related resources outside their region. Crucially, these organisations cannot or at least do not sufficiently accomplish such access with unsubsidised collaboration. The subsidisation of joint R&D projects seems to be an effective tool for innovation stimulation in this case. However, our results also call for more research on this issue.

The findings for betweenness centrality are also difficult to be considered in policy design. This is because regions' betweenness centrality defies central planning: Betweenness centrality cannot be directly considered in or directly influenced by R&D subsidisation policies, as a particular region's betweenness centrality emerges as a feature of the total network. Accordingly, the finding calls for a system (network) perspective on the subsidisation of joint R&D projects, which has yet to be developed.

5.7 Summary and conclusion

So far, studies on the effects of public (collaborative) R&D subsidies predominantly focus on the inflow of monetary resources into firms linked to the successful acquisition of subsidies. The literature is particularly concerned about whether subsidies partly crowd out private sector R&D investments or not (cf. Zúñiga-Vicente et al. 2014). However, the insight that R&D subsidies are increasingly granted to joint R&D projects demands for a more differentiated analysis on this type of policy tool (Czarnitzky and Fier 2003, Fornahl et al. 2011, Broekel 2013).

The paper at hand contributes to this discussion and puts forward the existence of at least two effects being related to the subsidisation of joint R&D projects that are rarely discussed in the existing literature. The first effect concerns the access of organisations to additional resources by participating in subsidised joint R&D (*collaboration effect*). This effect (which to some extent overlaps with the cooperation additionality argument by Wanzenböck et al. (2013) is conditional on the type of resources subsidised collaboration add to joint projects, whereby particularly related inter-regional resource combinations are argued to be most valuable. The second effect emerges as a consequence of subsidised collaboration: Organisations become embedded into (subsidised) inter-organisational R&D collaboration networks (*network effect*) and thereby gain access to knowledge diffusing therein. We argue that traditional evaluation approaches at the firm-level are likely to miss these two effects and, in addition to explicitly consider firm-level effects, such evaluation approaches should be complemented by studies on more aggregated (innovation system) levels.

These arguments are backed by means of an empirical study investigating the relevance of these effects in the development of German regions' innovation growth between 1999-2003 and 2004-2008. The results show that regions can improve innovation output when collaborative R&D subsidies provide access to related resources, as these allows for combining distant but not too distant knowledge (Frenken et al. 2007).

The paper moreover shows that centrality in subsidised cross-regional R&D collaboration networks gives access to valuable knowledge spillovers. Hence, the paper shows that there are strong indirect effects related to the subsidisation of joint R&D projects that are rarely considered in the existing literature.

The empirical study has a number of shortcomings that need to be discussed. They particularly concern unobserved R&D collaboration and networks. In this sense, our results remain somewhat difficult to interpret, as unobserved R&D collaboration are a crucial omitted variable and hence a potential source of biases. Future studies might have the possibility to draw on even more comprehensive databases and overcome this shortcoming. Another data-related problem concerns the limitation of the data source to R&D subsidies by the federal government in Germany. Unfortunately, no information is currently available on R&D subsidies by the federal states, which are however also important sources of R&D subsidisation.

Despite these restrictions, the present study has a number of important implications. First of all, it shows that subsidies for collaborative R&D do impact regional R&D activities. However, their impact strongly depends on whether collaboration created by R&D subsidies are additional to unsubsidised R&D collaboration or whether they represent collaborations that would have been realised anyhow without subsidies. If it is the case, and this is still to be shown by future research, that they are additional to unsubsidised ones, the granting of subsidies to collaborative R&D should be extended, as currently just about one third of all R&D projects subsidised by the federal government of Germany are joint projects (Broekel and Graf 2012). Second, the effectiveness of R&D subsidies for joint R&D strongly depends on the right combination of organisations teaming up. Hence, partner choice is brought into the context of R&D subsidisation and consequently should become a central element of R&D policy. The study shows that this goes beyond simply mixing public research organisations and private firms. Third, we show that firm-level studies evaluating R&D subsidies can and should be complemented by empirical studies at other levels. Given the strong relevance of territorial innovation policies in subsidisation schemes, this particularly concerns the regional level.

Appendix A5

Industry	Dummy (Broekel 2007)	Industry (Schmoch et al. 2007)	NACE	Description
1	1	1	15	Food beverages
2	1	2	16	Tobacco products
3	1	3	17	Textiles
4	1	4	18	Wearing apparel
5	1	5	19	Leather articles
6	1	6	20	Wood products
7	1	7	21	Paper
		8	22	Publishing, printing
8	2	9	23	Petroleum products, nuclear fuel
9	2	10	24.1	Basic chemical
9	2	11	24.2	Pesticides agro-chemical products
9	2	12	24.3	Paints, varnishes
9	2	13	24.4	Pharmaceuticals
9	2	14	24.5	Soaps, detergents, toilet preparations
9	2	15	24.6	Other chemicals
9	2	16	24.7	Man-made fibers
10	2	17	25	Rubber and plastics products
11	3	18	26	Non-metallic mineral products
12	3	19	27	Basic metals
13	3	20	28	Fabricated metal products
14	3	21	29.1	Energy machinery
14	3	22	29.2	Non-specific purpose machinery
14	3	23	29.3	Agricultural and forestry machinery
14	3	24	29.4	Machine-tools
14	3	25	29.5	Special purpose machinery
14	3	26	29.6	Weapons and ammunition
14	3	27	29.7	Domestic appliances
15	4	28	30	Office machinery and computers
16	4	29	31.1	Electric motors, generators, transformers
16	4	30	31.2,31.3	Electric distribution, control, wire, cable
16	4	31	31.4	Accumulators, battery
16	4	32	31.5	Lightening equipment
16	4	33	31.6	Other electrical equipment
17	5	34	32.1	Electronic components
17	5	35	32.2	Signal transmission, telecommunications
17	5	36	32.3	Television and radio receivers, audiovisual electronics
18	5	37	33.1	Medical equipment
18	5	38	33.2	Measuring instruments
18	5	39	33.3	Industrial process control equipment
18	5	40	33.4	Optical instruments
18	5	41	33.5	Watches, clocks
19	6	42	34	Motor vehicles
20	6	43	35	Other transport equipment
21	1	44	36	Furniture, consumer goods

Appendix A5-1. Overview industries.

	min	max	mean	median	sd
PATENTS growth rates	-2.55	1.534	-0.420	-0.413	0.529
PATENTS (99-03)	5.020	14363.212	232.532	57.534	661.724
PATENTS (04-08)	5.008	10183.554	163.910	41.280	454.862
R&D EMPL	7.500	128259.384	2471.219	881.162	6156.417
PUBLICATIONS	0.000	7.878	3.656	3.621	2.512
POP.DEN	3.903	7.432	5.432	5.327	0.645
HERFINDAHL	0.060	0.517	0.119	0.094	0.071
HERFINDAHL^2	0.004	0.267	0.019	0.009	0.033
EAST.dummy	0.000	1.000	0.136	0.000	0.343
SUBS.INDI	0.000	38.000	0.656	0.000	2.584
SUBS.COLL	0.000	93.000	2.810	0.000	7.793
SUBS.INDI (90-98)	0.000	128.000	2.838	0.000	8.857
SUBS.COLL (90-98)	0.000	95.000	2.397	0.000	7.396
PATENTS.spatial	9.573	1214.134	270.835	230.640	179.705
PATENTS.relational	0.000	7256.743	446.727	0.000	701.915
REG.COLL	0.000	70.000	2.131	0.000	5.545
INTER.COLL	0.000	2976.000	31.856	0.000	133.667
BETWEENESS	0.000	612.715	53.956	25.362	73.039
SIM.REG	0.000	48.000	1.305	0.000	2.855
SIM.INTER	0.000	8.686	0.327	0.000	0.757
SIM.REG^2	0.000	2304.000	9.847	0.000	87.177
SIM.INTER^2	0.000	75.4514	0.679	0.000	3.318

Appendix A5-2. Descriptives.

	gl	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) PATENTS (99-03)	-0.232																	
2) PATENTS (04-08)	-0.152	0.984																
3) R&D EMPL	-0.143	0.775	0.795															
4) PUBLICATIONS	-0.103	0.256	0.256	0.222														
5) POP.DEN	-0.190	0.248	0.237	0.259	0.585													
6) HERFINDAHL	0.032	-0.061	-0.055	-0.090	-0.192	-0.199												
7) EAST	0.089	-0.070	-0.068	-0.081	0.081	-0.177	-0.174											
8) SUBS.INDI	-0.126	0.539	0.522	0.344	0.233	0.156	-0.056	0.014										
9) SUBS.COLL	-0.100	0.619	0.630	0.530	0.264	0.209	-0.083	0.058	0.675									
19) SUBS.INDI (90-98)	-0.125	0.663	0.675	0.595	0.220	0.182	-0.091	0.087	0.654	0.737								
11) SUBS.COLL (90-98)	-0.106	0.627	0.636	0.567	0.252	0.216	-0.079	0.033	0.699	0.930	0.756							
12) PATENTS.spatial	-0.021	0.025	0.027	-0.025	0.072	0.159	0.121	-0.301	-0.018	-0.027	-0.058	-0.025						
13) PATENTS.relational	-0.111	0.245	0.252	0.233	0.197	0.212	-0.017	-0.010	0.224	0.357	0.279	0.317	0.040					
14) REG.COLL	-0.068	0.472	0.485	0.463	0.331	0.233	-0.114	0.170	0.532	0.728	0.614	0.687	-0.081	0.319				
15) INTER.COLL	-0.073	0.509	0.523	0.532	0.211	0.201	-0.070	0.005	0.423	0.726	0.604	0.685	-0.014	0.220	0.688			
16) BETWEENESS	-0.065	0.205	0.211	0.202	0.350	0.320	-0.090	0.002	0.219	0.298	0.234	0.263	0.023	0.370	0.254	0.169		
17) SIM.REG	-0.067	0.209	0.215	0.185	0.094	0.134	-0.040	-0.018	0.306	0.417	0.317	0.364	0.016	0.401	0.133	0.210	0.339	
18) SIM.INTER	-0.058	0.380	0.393	0.318	0.219	0.210	-0.071	0.024	0.411	0.628	0.465	0.562	0.011	0.464	0.443	0.550	0.287	0.544

Appendix A5-3. Correlations.

Chapter 6

The rise and fall of occupational specialisations in German regions from 1992 to 2010 – Relatedness as driving force of human capital dynamics

6.1 Introduction

The distribution of human capital in space is diverging. Within many industrialised countries such as the US, Germany and Canada, initially high skilled regions in the 1970s became increasingly skilled in the periods afterwards (Glaeser and Berry 2005, Shearmur and Polèse 2007, Poelhekke 2013). This divergence comes along with positive effects of high skilled regions on growth in population, employment and income. To the contrary, regions with less skill endowment stagnate or even decline (Florida et al. 2008). Thus, there is a rise of the skilled region (Glaeser and Saiz 2004).

Different approaches offer explanations for the spatial distribution of human capital. Glaeser et al. (2001) argue that higher initial levels of regional human capital become self-reinforcing over time. Shapiro (2006) adds the importance of local amenities. Florida (2002, 2004) emphasises the role of regional tolerance and openness to diversity. More recent studies, however, shifted their focus to the composition of the regional skill structure itself. Glaeser and Resseger (2010) find that skills have more impact in larger regions. Poelhekke (2013) states that regional success depends on attracting the right combination of regional skills. This is in line with Florida et al. (2008) who find that regional skill accumulation is driven by the *interplay* of people holding different skillintensive occupations.

The relevance of the interplay of the skill structure for the regional human capital accumulation can also contribute to the evolutionary understanding of regional development. Herein, skill accumulation is characterised as a localised, cumulative and interactive process (Boschma and Lambooy 1999). Recent research efforts further show that interactions among economic actors are most beneficial, when they share related knowledge. Related knowledge is characterised by a certain degree of cognitive distance that enables effective communication, but not too low cognitive distance to avoid lock-in (Nooteboom 1992, 2000). Cognitive distance arises in multiple dimensions as people develop along different environments. So far most studies have interpreted the concept with regard to contents in technological or industrial knowledge (Neffke et al. 2011, Boschma et al. 2015). This has neglected the role of relatedness in occupational structures for regional development. Occupations reveal a human capital driven way of how people percept, interpret and evaluate knowledge (Thompson and Thompson 1985, Markusen 2004). Aggregated to the regional level cognitive distance in occupational structures offers potentials but also puts constrains on regional human capital accumulation through its effect on localised human capital externalities. In addition to that, the occupational composition of regions may also constrain the ease with which regions can shift to new sets of occupations (Muneepeerakul et al. 2013, Shutters et al. 2015). This is because of the relevance of relatedness of regional structures for future geographical diversification (Hidalgo et al. 2007).

As a consequence, this paper contributes to the understanding of why and how skills accumulate in regions by adopting a relatedness perspective. It is argued that the occupational composition of a region matters for dynamic regional skill accumulation via its effect on the entry (exit) of related (unrelated) occupational specialisation. That is, the current occupational composition places a region in a so-called *occupation space* that determines future regional diversification possibilities. The main claim of the paper is that the rise and fall of occupations and hence the regional human capital dynamics is driven by the degree of relatedness of occupations in space. Hence, related variety in occupations spurs entry into new sets similar occupations and fosters regional skill accumulation.

The empirical results confirm the proposed relationship between occupational relatedness and the regional entry into new and exit from occupational specialisations. The analysis for German labour market regions in the period 1992 to 2010 shows that the probability of entry into new occupational specialisations increases with the degree of relatedness around an occupation. This effect is even more pronounced when considering human capital intensive occupations. Next, relatedness also preserves regions from exits of occupational specialisations. The results indicate a negative relationship between regional occupational relatedness and the probability of exit of an occupation in a region. Hence, occupational relatedness and regional occupational structures are driving forces of dynamic skill accumulation of regions.

6.2 Skill accumulation and related occupational diversification in regions

Human capital takes a central role in the economic development of nations (Barro 1991) as well as regions (Rauch 1993, Simon 1998). Insights from endogenous growth theory highlight that the clustering effect of human capital facilitates knowledge spillovers and innovation (Lucas 1988). Thus, dense urban regions reduce the costs of knowledge transfer by allowing ideas to move more quickly (Florida et al. 2008). In support of this, Glaeser and Mare (2001) find a higher wage growth of workers coming to in US metropolitan areas. This suggests a faster human capital accumulation in dense urban areas. Two mechanism may contribute to this pattern. First, workers may benefit from the ability to learn from each other, thus there is faster learning in cities (see also Glaeser and Resseger 2010). Second, workers may increase wages and productivity due to an increasing job mobility in dense areas. This may result in better matching in skills.[29]

Relatedness is found to have an effect on both of these mechanisms. First, the concept of related variety stresses the fact that knowledge spillovers across industries require a certain degree of cognitive proximity (Frenken et al. 2007, Quatraro 2010). Second, relatedness matters for the effects of labour mobility via the type of skills that are brought to recruiting firms. When focussing on related variety in educational skills Boschma et al. (2009) and Boschma et al. (2014a) find that only when new employees bring in skills that are related to

[29] An alternative explanation on how human capital affects regional development and human capital accumulation is offered by Shapiro (2005). While consistently finding that human capital is causing regional employment growth, Shapiro (2005) highlights additional effects coming from a higher growth in the quality of life through the availability of consumer amenities.

the existing skill portfolio of plants, plants and the region in general benefit from the presence of labour mobility.

Beyond the focus on wages and productivity, human capital is supposed to be a factor also for long-term regional development. Glaeser (2005) uses the example of Boston to highlight that skilled workers have been a source of long-run regional health for almost 400 years. Long-run regional development means successfully responding to challenges. Thereby the rise and fall of regions hinges on their ability to re-orient. Human capital might be most valuable in these cases because 'skills create flexibility and the ability to reorient towards a new urban focus' (Glaeser 2005, p. 122).

Competing theories present explanations for the trend of high skilled regions to become more skilled over time. Berry and Glaeser (2005) present insights that it is the initially higher endowment with human capital that allows regions to become more skilled over time and that this contributes to an increasing segregation by skills in space. One mechanism that explains this relationship is the tendency of skilled entrepreneurs and managers to innovate in ways that increasingly employ skilled workers. Thus, there is an increasing demand for skilled workers in initially high skilled regions. A second explanation lies in higher initial advantages due to the presence of higher education institutions. Moretti (2004) argues that universities matter here because they reflect a long term regional commitment to education.

Florida (2002) presents a complementary view on regional human capital accumulation. While the majority of empirical studies on the regional human capital distribution focus on level of education of the people in a region, Florida (2002) uses occupations instead.[30] Following Thompson and Thompson (1985) he argues that education measures the available stock of human capital in a region. Contrary, adopting an occupational lens on regional economic structures allows analysing what people actually do with their level of education (see also Feser 2003, Markusen 2004, Barbour and Markusen 2007, Currid and Stolarick 2010). The occupational approach allows Florida (2002) first to show that regional tolerance is related to the spatial concentration of talented people. Subsequently, Stolarick and Florida (2006) demonstrate the importance of occupational diversity on human capital externalities and their leverage effect on human capital in a region.

The occupational lens brings up the specific regional skill structure as a potential driver the spatial distribution of human capital. Indeed, Ellison and Glaeser (2010) show that labour pooling can work across sectors if sectors use workers with similar skills and that this drives agglomeration both of industries and skills. Otto et al. (2014) use of concept of skill-relatedness to demonstrate how regional resilience depends on the extent to which industry-specific human capital can be redeployed across industries in a region. Muneepeerakul et al. (2013) and Shutters et al. (2015) find that the current set of occupational specialisations of a region and its location in the occupation space constrain its future development paths. This is line with more general insights in the relatedness literature that puts emphasis on how regional economic structures affect the dynamics of regional development. The relatedness

[30] Both measures can be grounded in the seminal work of Gary Becker. Becker (1975) emphasises that education *and* training on the job are the most important components of human capital formation. Shapiro (2005) and Simon and Nardinelli (2002) also apply occupational approaches but use occupations as a proxy for education.

concept sees regions as networks linking specialised production units in space (Muneepeerakul et al. 2013). What types of goods and services at which level of quality regions can offer is largely determined by their underlying set of industries, technologies and skills. They position a region in a globally determined *product*, *industry* or *technology space* (Hidalgo et al. 2007, Shutters et al. 2015). The position in the space constrains future regional development (Hidalgo et al. 2007, Neffke et al. 2011, Boschma et al. 2013, 2014b, 2015).

Yet, little research efforts have been made on how relatedness shapes the spatial distribution of human capital. However, the underlying concept of cognitive distance and the regional dimension of occupational diversity make relatedness also subject matter for human capital accumulation. This leads to the assumption that rise of the skilled region may be driven by rise and fall of specific occupations that are dependent upon the degree of relatedness of regional occupational structures. However, occupational relatedness in space is driven by at least two dimensions of organising production of knowledge and goods. Following Breschi et al. (2003) one can theoretically distinguish occupational similarity and complementarity.

Occupational similarity

Different occupations yield cognitive distance between individuals. Thereby, occupations with high similarities may produce relatedness patterns because of people locating in regions with an abundance of similar jobs to have the best chances of employment and to better handle regional employment shocks (Overman and Puga 2010). To the contrary, increasing cognitive distance determines the novelty generation potential of individual interactions. Novelty generation is thereby a function of the skill intensity of occupations (Gathmann and Schönberg 2010). Given this, occupational similarity fosters learning via unintended (spillovers) or intended (localised) learning processes (Breschi et al. 2003) especially when individuals interact that hold skill-intensive occupation. Unintended knowledge spillovers relate to the fact that knowledge spills over in various way. This may happen when individuals or more aggregated firms benefit from 'spill-acrosses' generated by the regional presence of different communities of practice such as engineering, IT, arts, culture, management or finance (Stolarick and Florida 2006).

Moreover, localised learning may reflect intended ways of knowledge generation where individuals and firms seek places where skills are available. This may reflect Florida's (2002) notion of cities or regions are increasingly becoming places of skills. Gabe and Abel (2015) add to this point when showing that occupations with similar knowledge profiles exhibit higher degrees of regional co-specialisation. Thus, localised learning may result from the regional interaction of individuals approaching similar technological domains from different occupational perspectives. To work with an example, although holding different occupations, environmental economists may benefit from the regional presence of environmental planners, engineers and ecologists in order to face similarities in environmental problems solving. Hence, the occupational composition of regions reflects intended outcomes of innovative activities and interdependencies needed to realise novel tasks (Shutterns et al. 2015).

Occupational complementarities

Occupational relatedness also reflects the needs for division of labour in the organisation of production. Doctors, nurses, lab assistant and pharmacists may exemplify this division in the field of medicine. Organisation science more generally refers to this topic as technical interdependencies among jobs. The notion technical addresses to the content and interdependency the level of cooperation and coordination required to perform a task (Hasan et al. 2015). Firms in regions develop routines to structure their complex operations and to make them more predictable (Nelson and Winter 1982). Durable routines create occupational relatedness that reflects the need for complementarities from the point of organisation (Milgrom and Roberts 1990, Pavitt 1998)

As a result, regional occupational structures reflect occupational relatedness due to intended and unintended inter-occupational learning processes needed to realise novel tasks (Florida et al. 2008). The corresponding externalities may act as incentive and selection mechanism for individuals and firms (Boschma 2004). Hence, the regional skill structure itself may leverage regional human capital accumulation due to the interdependency of occupations in space (Currid-Halkett and Stolarick 2011). Next to that, occupational relatedness also reflects complementarities without specialised occupations cannot fulfil their specific tasks and to a certain degree similarities when different occupations are characterised similar task requirement (Shutterns et al. 2015). Since, all these aspects are putting constrains the process of the diversification of regions into new sets of occupations, regions will move into related occupations rather than unrelated ones. However, to identify whether occupational relatedness drives regional human capital accumulation, human capital intensive occupations first have to attract each other by showing higher degrees of interdependency in space. Second, occupational relatedness has to affect the dynamics of the regional composition with occupations via the entry and exit of new set of occupations. This affect should go beyond the effects of educational measures of human capital to highlight the effects of the regional occupational mix. This two aspects will now be tested by applying methods recently developed by Hidalgo et al. (2007), Muneepeerakul et al. (2013) and Boschma et al. (2015).

6.3 The underlying dataset

The empirical analysis uses information about the spatial distribution of employees subject to social security contributions in the German manufacturing sector in the period 1992 to 2010. The data are provided by the Federal Agency on Employment of Germany. To avoid disturbances by atypical types of work (such as mini-jobs and inters) the focus is on individuals holding regular jobs subject to social security contributions without special features. Because of changes in the in the SIC system for Germany, the analysis is restricted to all employees working in the manufacturing sector given the respective classification in a year.[31] Individual occupational information is based on the 1988 edition of the German Classification of

[31] In the period of analysis employment data were classified in four different industrial classifications. These include the German Classification of Economic Activities 1979 (for the years 1992-1999), 1993 (for the years 2000 to 2003), 2003 (for the years 2004 to 2008) and 2008 (for the years 2008 onwards). While there are substantial changes in the grouping of industries among different levels of disaggregation over time, their classification in the broad category of manufacturing remains rather stable. To be included in the analysis, employees had to work in the section (the highest level of disaggregation in the German industrial classification) of manufacturing at the respective time.

Occupation (KldB 1988). This classification remains unchanged over the whole period of analysis and is structured as follows. First, it distinguishes 33 occupational segments characterised by various criteria (e.g. activity, type of material processed, object of work). The 2-digit level consists of 86 occupational groups bringing together occupations that are functionally related by their occupational task and activity. The analysis makes use of data at the 3-digit level providing for each German labour market region the number of employees in 319 occupational orders. Occupational orders define similar occupational activities as independently as possible from their qualification and position within the company. For their classification it is irrelevant how individuals have gained their professional skills, the distinguishing feature is the occupational activity an individual performs, independent from the level of formal qualification or the quality requirements of the task (Paulus and Matthes 2013).

The data provided by the Federal Agency on Employment of Germany additionally include information about the individual educational attainment. This information is used to compute alternative measures of regional human capital endowment. Furthermore, this information enters the analysis in an aggregated form to gain information on the human capital intensity at the occupational level. Data on the sectoral affiliation can be used to exemplify industry specific occupational characteristics. However the industrial classification is subject to substantial changes making comparison over time difficult.

6.4 Measurement of interdependency of occupations in space

There exist many ways of measuring relatedness. The measures can generally be grouped into three categories. First, *categorical measures* rely upon researcher judgment to identify the degree of commonality between pair of economic activities. However, the subjective nature of relatedness judgments makes these measures open to bias when putting emphases on different category specifications (Bryce and Winter 2009). Next, *standard industrial classification* (SIC) *based measures* derive relatedness on the assumption that two economic entities sharing the same SIC code show a certain degree of commonalities (Frenken et al. 2007). Also these measures suffer from several shortcomings. Varying degrees of breadth in the SIC system can produce artificially high (low) numbers of relatedness as result of more fine (coarse) graded classifications. Furthermore SIC based measures place equal dissimilarity between and relatedness values within SIC classes. They are subject to classification errors and exclude dynamic degrees of relatedness between economic entities (Farjoun 1994). Tanriverdi and Venkatamaran (2005) additionally emphasise that SIC based measures do not allow insights into the types of the underlying relatedness as the effects depend on a consistent application of the classification rule throughout the whole classification system.

Most of the recent studies apply *revealed relatedness measures.* Revealed relatedness measures define relatedness through co-occurrences focusing on how often two economic entities are found together in specific fields of economic activity. The number of co-occurrences is usually adjusted by a comparison to a random distribution. The paper follows this approach. Occupational relatedness in space is determined in line with Muneepeerakul et al. (2013). They use the co-occurrence of two occupational specialisations in a region as measure of occupational interdependency. This interdependency provides the base for an aggregate measure of relatedness that is calculated at the regional level. To derive this measure, Muneepeerakul et al. (2013) start with the calculation of the locations quotient $LQ_i^{(m)}$

$$(6.1) \qquad LQ_i^{(m)} = \frac{(x_i^{(m)} / \sum_i x_i^{(m)})}{\sum_m x_i^{(m)} / \sum_m \sum_i x_i^m}$$

where $x_i^{(m)}$ is the number of employees in occupation *i* and labour market region *m*. Values of LQ_i larger than 1 imply that labour market region *m* is specialised in this occupation, meaning that a region *m*'s share in occupation *i* is higher than that of the average region.[32] To capture the relationship between two occupations in space Muneepeerakul et al. (2013) define *interdependency* (ϕ) between occupations *i* and *j* as:

$$(6.2) \qquad \phi_{ij} = \frac{P\left[LQ_i^{(M)}>1, LQ_j^{(M)}>1\right]}{P\left[LQ_i^{(M')}>1\right] P\left[LQ_j^{(M'')}>1\right]} - 1,$$

where *M*, *M'*, *M''* are randomly selected labour market regions. The sign of ϕ indicates the kind of spatial interdependencies between the two occupations with

$$\phi_{ij} > 0 \quad - \quad occupations\ i\ and\ j\ are\ positively\ related$$
$$\phi_{ij} = 0 \quad - \quad occupations\ i\ and\ j\ are\ independent$$
$$\phi_{ij} < 0 \quad - \quad occupations\ i\ and\ j\ are\ negatively\ related.$$

ϕ allows judgements about whether the co-specialisation of these occupations follows a rather supportive or conflictive relationship with values of -1 indicating that occupations *i* and *j* are never co-specialised in the same region. By comparing the pairwise conditional probabilities with their marginal probabilities respective values of ϕ can be interpreted in comparison to independently distributed occupational specialisations in space. By construction ϕ_{ij} is symmetric (ϕ_{ij} = ϕ_{ji}) and allows a network representation of the interdependency of occupations in space.

6.5 The occupation space

Figure 6-2 visualises the network of occupations generated by the help of the interdependency values from equation 2. The *occupation space* reflects the degree of non-random regional co-specialisation of occupations in the German manufacturing sector in 2010. The histogram of ϕ (Figure 6-1) reveals that the majority of the occupational specialisations show a positive degree of interdependency at the dyadic level. Only roughly 1.0 percent of the values stick to the value of -1, whereby 19.4 percent of ϕ remain negative. These results are comparable to those obtained by Muneerpeerakul et al. (2013) for the United States, although the distribution obtained for German labour market regions has more weight on positive values

[32] The use of location quotients is not without shortcomings. First, there is no commonly agreed cut-off value for determining agglomeration. Values above 1 indicate that an occupation is 'over represented' in this area. Moreover, LQ's do not provide information about the absolute size of employees working in an occupation. High values might be driven by occupations with small numbers of employees in these occupations. In the robustness analysis these issues are addressed. They are not found to drive the results.

of ϕ. This might be a result of the more disaggregated level of analysis in Muneerpeerakul et al. (2013). They rely on 364 Metropolitan Statistical Areas and 787 distinct occupations classified by the U.S. Bureau of Labor Statistics.

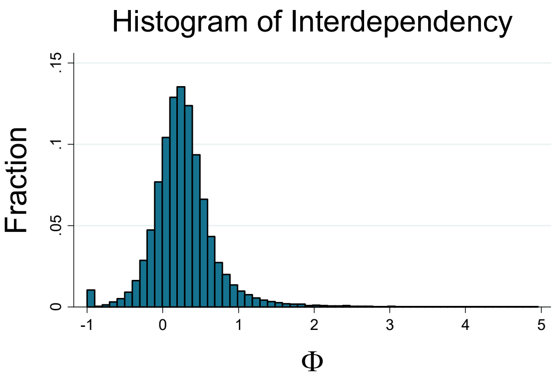


Figure 6-1. The occupation space. Histogram of ϕ. 72 (of 115934) very large values of ϕ were excluded for illustration reasons. These values are a result of uncommon occupations being specialised in the same labour market region.

Figure 6-2 allows detailed insights into the network representation of the occupation space. As there exists a substantial number of negligible low interdependency values, this illustration is based upon the top 5000 links between occupational orders. What a network representation can indicate becomes apparent when applying an occupational-functional perspective to the interdependency values. The aim here is to capture the skill content of occupations by grouping them into economic functions. The papers makes use of Blossfeld's Occupational Classification (1987). Blossfeld distinguishes between three upper level groups - production, services and administration - and secondly ranks occupations according to the type of skills required with

- Unskilled employees – Workers performing simple manual (*Sim_Manual_Occ*), service (*Sim_Service_Occ)* as well as administration tasks (*Sim_Admin_Occ*).
- Skilled employees – Workers performing qualified manual (*Qual_Manual_Occ*), routine service or (*Qual_Service_Occ*) administration (*Qual_Admin_Occ*) as well as complicated blue collar tasks (*Technicians*). This group also includes semi-professionals (*Semi-Professions*).
- Most highly skilled employees – Workers performing a high share of non-routine task such as mangers (*Managers*), engineers (*R&D_Occ)* and professionals (*Professions*).

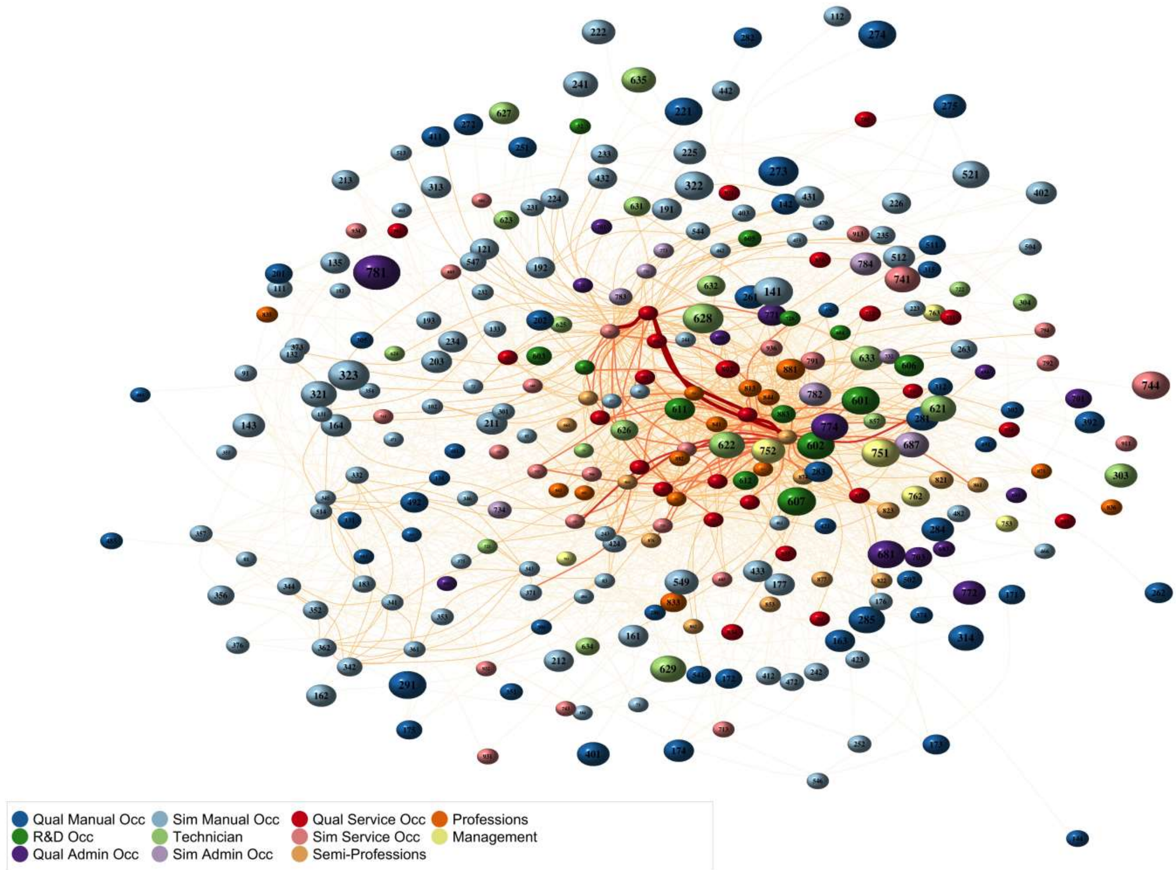


Figure 6-2. Network representation of the occupation space including the top 5000 links between these occupations. The strength of the link represents the interdependency value between two occupations. Notes are labelled with the number of their occupational order (Paulus and Matthes (2013) includes a detailed description). The size of the nodes indicates the share of employees in this occupation on all manufacturing employees, and the colour is chosen according to Blossfeld's Occupational Classification aiming to generate occupational groups by general qualification and skills as well as occupational duties.

The network representation shows that occupations with higher skill requirements are located more centrally in the space. This fact especially holds for R&D occupations such as several types of engineers, natural scientists[33] and for occupation typically related to a firms headquarter including management related occupations[34] as well as (high)-qualified service occupations[35]. Even more, the presence of thick red lines indicates strong dyadic interdependencies between these occupations in terms of co-specialisations in space. In sum, the core of the occupation space is characterised by highly interdependent skill-intensive occupations that provides the ground for related occupational diversification. Contrary the periphery of the occupation space is dominated by simple and qualified manual as well as simple service occupations (indicated by the light blue, blue and rose circles). Although being important in terms of relative employment shares, these occupations are characterised by low interdependency values indicating limited degrees of co-specialisation in space and larger distances to high-skilled occupations in the network. Furthermore the limited degree of

[33] 601 – mechanical, motor engineers; 602 – electrical engineers; 611 – chemists, chemical engineers; 612 – physicists, physics engineers, mathematicians.

[34] 751 – managing directors, divisional managers, entrepreneurs; 752 – management consultants, organisers.

[35] 774 – data processing specialists; 881 – Economic and social scientists; 813 – legal representatives, advisors.

interdependency makes these occupations more vulnerable with respect to regional occupational dynamics and poor candidates for regional development policies.

Figure 6-3 summarises the interdependency values ϕ by occupational functions. It confirms that the presence of high values (or darker colouring) along the diagonal is almost restricted to skilled and highly skilled occupations. This favours an occupational-ladder interpretation of the interdependency values indicating that co-occurrences of occupational functions are more probable in nearby skilled and highly skilled occupations within the upper level groups of production, services and administration. However, there remain substantial off-diagonal dark blue areas. They point towards strong interdependencies among skilled and highly skilled occupational functions across the upper level groups. This additionally allows a modular interpretation of the occupation space meaning that the co-occurrence of occupational specialisations is more likely within (highly)-skilled occupational categories, irrespective of performing production, service or administration task in manufacturing. Hence, there is a density effect for skill-intensive occupations. The contrary interpretation holds for the simple manual, service or administration categories. In general they are characterised by lower degrees of relatedness within their respective group. They also show lower values of relatedness with other categories of occupation functions in space meaning their interdependency with other occupational functions in space is rather weakly developed. This result is robust against a more fine graded industrial perspective. When performing this analysis at the 2-digit level within the manufacturing sector in 2010 and then aggregating these values in a similar way, the correlation between of values of both matrices is 0.88.

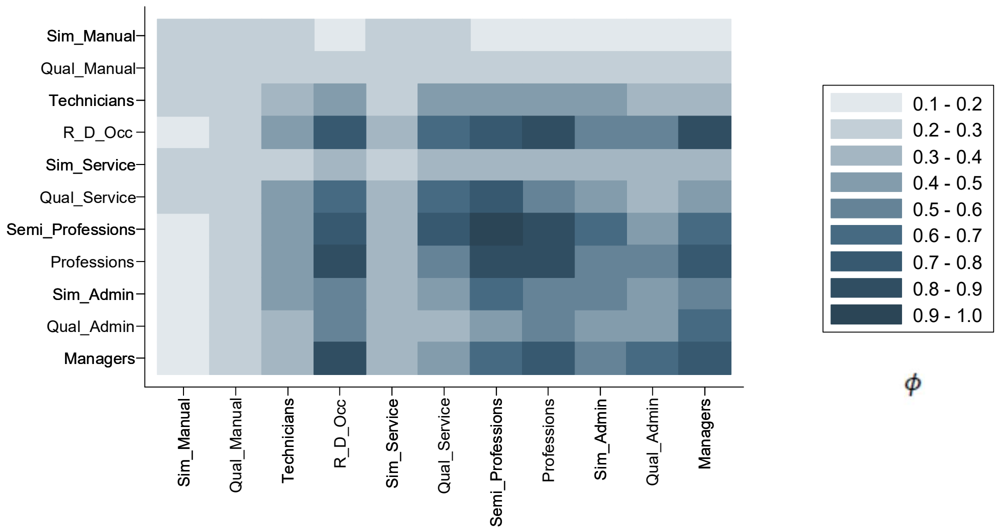


Figure 6-3. Mean interdependency ϕ within and between occupational functions according to Blossfeld's Occupational Classification.

Figure 6-4 highlights the dynamics of interdependency values ϕ within and between occupational functions between 1995 and 2010. Blank fields point to negative changes while the darker colouring points out increasing values of interdependency in this period. Figure 6-4 complements Figure 6-3 by showing that the dynamics of interdependency values favour occupational functions with higher skill levels. This especially holds within production related service occupations but also across functions with higher skill levels. Contrary, simple (*Sim_Manual_Occ*) or qualified manual production tasks (*Qual_Manual_Occ*) loose interdependency in space with highly skilled occupational functions such as mangers (*Managers*), engineers (*R&D_Occ*) and services in general (with exception of simple services). These groups only show increasing values of interdependency with functions holding similar skill average skill levels.

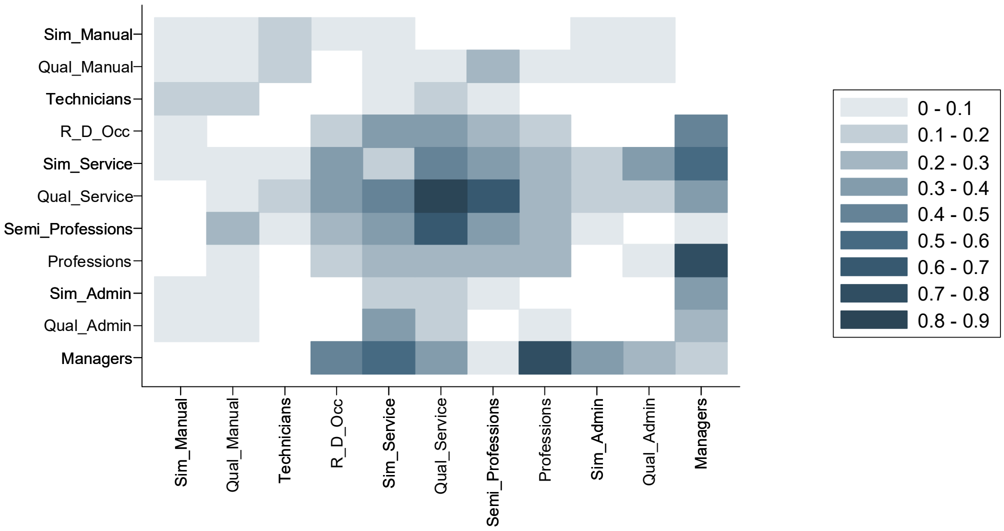


Figure 6-4. Factor of growth of mean interdependency ϕ within and between occupational functions in the period 1995 to 2010. Blank fields point to negative values of the growth factor.

6.6 Measurement of occupational relatedness of regions

While ϕ offers insights into the dyadic spatial interdependency of occupational specialisations in German manufacturing, relatedness in this understood as the aggregate degree of interdependency of an occupation to the regional set of occupational specialisation. This section tests whether German labour market regions enter (exit) occupational specialisations that are related (unrelated) to the existing set of occupational specialisations in a region. In line with Hidalgo et al. (2007), relatedness ω is calculated by the density around a new occupational specialisation *j* in region *m*

$$(6.3) \qquad \omega_j^m = \frac{\sum_i x_i \phi_{ij}}{\sum_i \phi_{ij}}$$

with ω_j^m being the degree of relatedness of occupation *j* given the structure of occupational specialisation of labour market region *m* with x_i = 1 if LQ_{mi} > 1 and 0 otherwise. A high relatedness value implies that region *m* has many specialised occupations surrounding occupation *j*.

To test this relationship, the paper adopts a dynamic perspective and studies the diffusion of occupational specialisation in four consecutive periods (1992-1995, 1995-2000, 2000-2005 and 2005-2010). Herein, "*Entries into specialisations*" are considered as those with an LQ_j < 0.5 at the beginning of each period and an LQ_j > 1 at the end of the periods mentioned above.

The control group refers to "*Underdeveloped occupations*" and is defined as those occupations that show values of LQ_j < 0.5 at both points in time. The contrary holds for "*Exits from specialisation*". They are defined by values of LQ_j > 1 at the beginning of each period and LQ_j < 0.5 at the end of the periods. The respective control group with occupations "*remaining specialised"* shows values of LQ_j > 1 at both points in time. Occupations that don't show this transitions are excluded from this step of the analysis.

Figure 6-5 indicates differences in the distribution of the density functions for entries in and exists from occupational specialisations in German labour market regions in the period 2005 to 2010. Starting first with the analysis for entries, part 6-5.A shows that distribution of relatedness values for *entries into specialisations* is shifted slightly to the right compared to the distribution of underdeveloped occupations. This shift is significant as indicated by Two-Sample Kolmogorov-Smirnov test for the equality of distribution functions (combined K-S: 0.1203***). However, the driving forces behind these shifts in the distributions are occupations belonging to group of high skilled occupational functions. As illustrated by three function-specific figures for *R&D occupations* (combined K-S: 0.3286***), *Professions* (combined K-S: 0.2700***) and *Managers* (combined K-S: 0.3305***), the distribution of *"Entries into specialisations"* clearly have more weight on higher relatedness values than those of underdeveloped occupations.[36]

Part 6-5.B allows similar insights for exits from occupational specialisations. Likewise entries, the two distribution functions differ from each other with the relatedness distribution for exists showing more weight on lower relatedness values than those occupations remaining specialised in the respective labour market regions (combined K-S: 0.0663***). Just as above, the main drivers behind these diffusion patterns are the high-skilled occupational functions (*R&D occupations* - combined K-S: 0.2541***, *Professions* - combined K-S: 0.2078*** and *Managers* - combined K-S: 0.3613***). However, the shift to lower values in relatedness for exits equally holds for all other occupational functions with a varying strength in the differences, typically related to the skill level of the occupational function.[37] Robustness checks further show that these results are robust against specific time effects with minor exceptions in the period 1992-1995, the period related to the strong restructuring in the economy after the German reunification.

[36] *Sim_Manual_Occ* - combined K-S: 0.1061***; *Qual_Manual_Occ* - 0.1677***; *Technicians* - combined K-S: 0.2135***; *Sim_Service_Occ* - combined K-S: 0.1182***; *Qual_Service_Occ* - combined K-S: 0.1788***; *Semi-Professions* - combined K-S: 0.1003*; *Sim_Admin_Occ* - combined K-S: 0.1839**; *Qual_Admin_Occ* - combined K-S: 0.1817***.

[37] *Sim_Manual_Occ* - combined K-S: 0.0495*; *Qual_Manual_Occ* - 0.0854**; *Technicians* - combined K-S: 0.1676***; *Sim_Service_Occ* - combined K-S: 0.0413; *Qual_Service_Occ* - combined K-S: 0.0747*; *Semi-Professions* - combined K-S: 0.1302**; *Sim_Admin_Occ* - combined K-S: 0.2435***; *Qual_Admin_Occ* - combined K-S: 0.2117***.

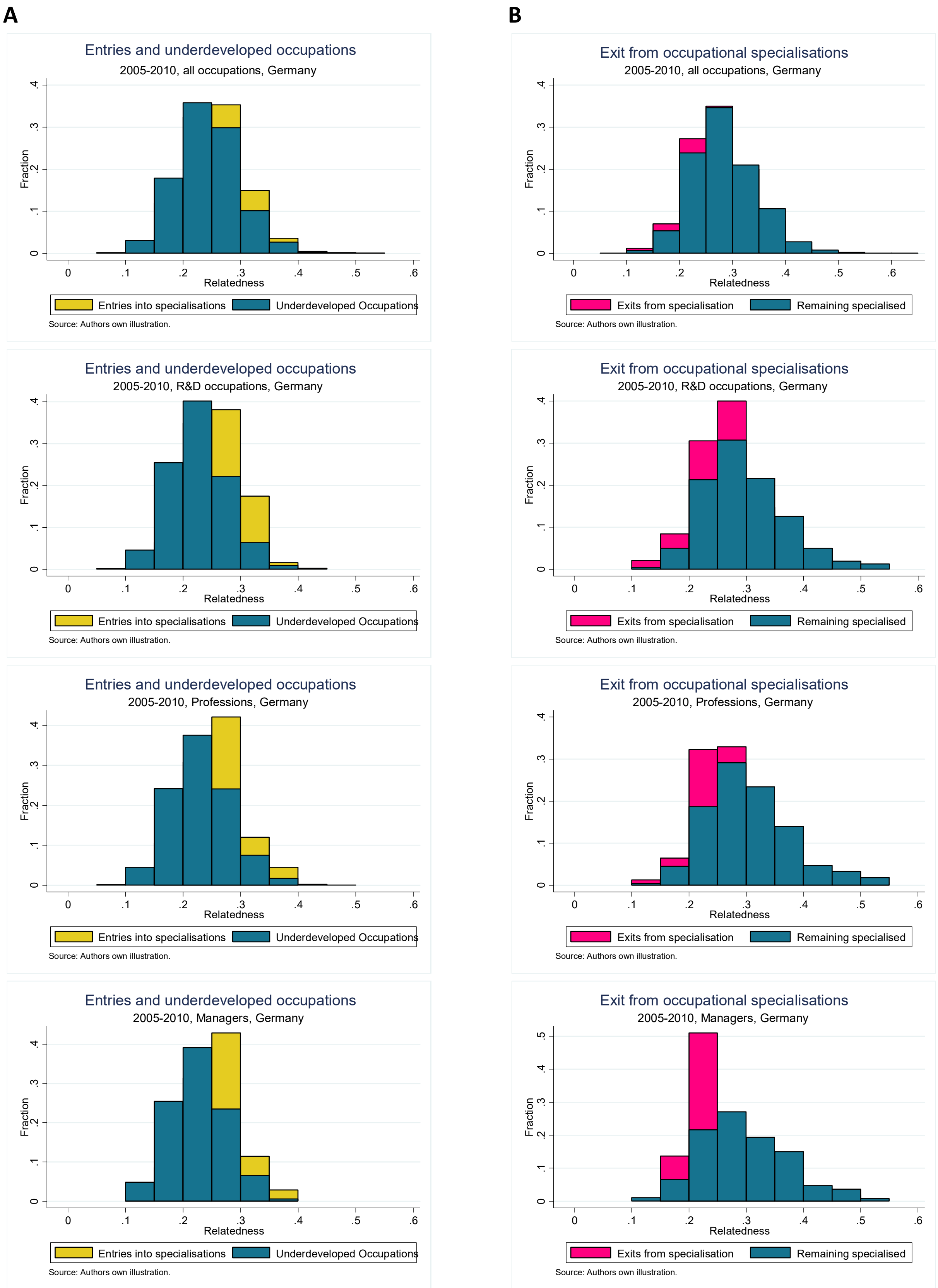


Figure 6-5. Evolution of occupational specialisations in German labour market regions from 2005 to 2010. **(A)** Distribution of relatedness ω for entries and underdeveloped occupations. **(B)** Distribution of relatedness ω for exits from and remaining specialised occupations. The results of (**A)** and **(B)** remain robust for all other periods under analysis.

6.7 Econometric specification

The next step tests the proposed relationship between occupational relatedness and the probability of entering and exiting occupational specialisation at the regional level. The econometric approach follows Boschma et al. (2015):

(6.4)

$$Entry_{j,m,t} = ß_1 Relatedness_{j,m,t-1} + ß_2 Region_{m,t-1} + ß_3 Occupation_{j,t-1} + \alpha_{j,m} + \delta_t + \varepsilon_{j,m,t}$$

where the dependent variable $Entry_{j,m,t} = 1$ if an occupation *j* that was not specialised in region m in time *t – 1* but enters in time t, and 0 otherwise. The main effect of interest comes from the variable $Relatedness_{j,m,t-1}$ which reflects the degree of relatedness of the occupation *j* in region *m* to the given set of occupational specialisations in this region in *t – 1*.

The regressions include a range of region and occupation specific controls. The vector $Region_{m,t-1}$ contains observable time-varying regional characteristics. It consists of the total number of employees in the region (*employment*) because larger regions show higher tendencies towards vertical disintegration (Barbour and Markusen 2007). Next, the share of employment in firms with less than 20 employees is used to control for internal economies of scale at the firm-level (*share20*). The ratio of people holding at least a university degree on the total number of employees (*hc_region*) controls for effects of the regional stock of human capital and thus allows a judgment whether relatedness in the occupational composition has an effect beyond measures of educational attainment. Last, the variable *specialisation*, measured by the Herfindahl-Index at the level of 19 sections[38] *z* is calculated as follows.

$$(6.5) \qquad Specialization_m = \sum_{z=1}^{19} a_{z,m}^2$$

Herein, $a_{z,m}$ denotes the share of section *z* in region *m* on the overall regional employment *a* of region *m*.

The vector $Occupation_{j,t-1}$ reflects observable time-varying characteristics at the level of occupations. It consists of the total number of employment in an occupation (*occ*) to control for the effects of the overall size of an occupation (see Boschma et al. 2015 for a similar approach). The human capital intensity of an occupation is measured by the share of employees holding a university degree on the total number of employees in this occupation. Last, $\alpha_{j,m}$ denotes an occupation-region-fixed effect, δ_t is time-fixed effect and $\varepsilon_{j,m,t}$ reflects the error term.

Similar to Boschma et al. (2015) this baseline specification results in a simple linear probability (OLS) regression. In addition to that the following tables also include static fixed effects panel models. Including fixed effects allows taking into account unobserved time invariant regional

[38] The sections reflect the lowest level of disaggregation in the German Classification of Economic Activities that is comparable of the period 1992 to 2010.

heterogeneity. Given this kind of specification, standard errors are clustered at the level of occupation-industries (Wooldrige 2003). The resulting panel consists of 270 German labour market regions, 319 occupations and four periods of analysis (1992-1995, 1995-2000, 2000-2005, 2005-2010) whereas *t* is the end date of each period and *t – 1* reflects the starting year. Table 6-1 presents descriptive statistics of the dependent (*entry* and *exit*) and independent variables used in the econometric models. The correlation matrix for both dependent variables can be found in Appendix A6-1.

Variables	N	Mean	SD	Min	Max
entry	167,602	0.051	0.220	0	1
exit	81,988	0.134	0.340	0	1
relatedness	167,602	0.248	0.055	0.092	0.509
ln_employment (region)	145,931	10.91	0.73	9.59	13.81
hc_region (region)	145,931	0.066	0.033	0.018	0.227
specialisation (region)	167,602	0.175	0.066	0.092	0.514
share20 (region)	167,602	0.331	0.067	0.126	0.565
ln_occ (occupation)	167,602	9.53	1.51	5.35	15.07
occ_hc (occupation)	167,602	0.125	0.241	0.000	0.971

Table 6-1. Summary statistics. Source: Author’s own calculation. Note that *employment* and *occ* enter the regression analysis log-transformed.

6.8 Results of the regression analysis

The first question addressed is whether German labour market regions indeed diversify into related sets of occupational specialisations. Table 6-2 presents the results. It distinguishes five different model specifications. Model 1 regresses the pooled relatedness indicator on the corresponding entry variables. Models 2 and 3 separately present the results for the effects for the regional and occupational controls. Model 4 includes the relatedness indicator, the regional and occupational controls. Model 5 is considered as the full model as it takes into account time and occupation-region fixed effects. The estimates show in all specifications a significant and positive effect of relatedness. When calculating the magnitude of this effect is becomes apparent that occupational relatedness is also quantitatively important for entries as elements of the occupational diversification of regions. Considering the coefficients of the full model in Table 6-2 (column 5), an increase in relatedness around a given occupation *j* by 10 % increases the probability of entry of this occupation by about 6.1 %.

The effects of regional and occupational controls further indicate that the size of an occupation positively affects the probability of entry in occupational specialisations at the regional level in all specifications. The larger an occupations becomes, the higher is the probability that it is becoming specialised. Human capital intensive occupations are found to have probabilities of entering specialisations, a fact that is consistent with higher spatial interdependencies between human capital intensive occupations. The set of regional control variables offers more differentiated results. While the effect of regional size is negative in all specification, meaning the larger a regions is, the less probable it shows entries into a new occupational specialisation, the coefficient remains significant only in the models without the full set of fixed effects. Similar to the regional size, human capital at the regional level measured by educational attainment has a positive effect on entry into new sets of occupational specialisation in Models 2 and 4. When considering the full model in column 5 the effect becomes insignificant. Last, the results of the full model in column 5 show that both regional specialisation and the share of people working in establishments with less than 20 employees exert significant positive effects on entries into new sets of regional occupational specialisations. On the one hand this supports the view that small firms are drivers of regional structural change (Nooteboom 1994). Otherwise this implies that regional specialisation goes in line with occupational specialisation, a fact that confirms the findings of Ellison et al. (2010) who show that industries employing the same types of workers tend to co-agglomerate.

Dependent variable is $Entry_t$	Model 1 – Relatedness	Model 2 – Adding regional controls	Model 3 – Adding occupational controls	Model 4 – Full model without fixed effects	Model 5– F.E.-Model
relatedness	0.309***	0.266***	0.322***	0.286***	0.121***
	(0.020)	(0.024)	(0.011)	(0.025)	(0.032)
ln_employment		-0.010***		-0.010***	-0.009
		(0.002)		(0.002)	(0.014)
hc_region		0.0641**		0.064**	0.074
		(0.030)		(0.030)	(0.092)
specialisation		-0.076***		-0.072***	0.147***
		(0.019)		(0.020)	(0.038)
share20		-0.001		-0.005	0.203***
		(0.019)		(0.020)	(0.049)
ln_occ			0.002***	0.002***	0.013***
			(0.000)	(0.000)	(0.003)
occ_hc			0.017***	0.018***	0.048*
			(0.002)	(0.003)	(0.028)
Constant	-0.026***	0.102***	-0.049***	0.083***	-0.139
	(0.005)	(0.023)	(0.005)	(0.022)	(0.166)
N	167,602	145,931	167,602	145,931	145,931
R^2	0.006	0.005	0.007	0.006	0.001
Period fixed effects	No	No	No	No	Yes
Region-occupation fixed effects	No	No	No	No	Yes

Source: Author's own calculation.

Notes: The dependent variable is entry = 1 of an occupation at the German labour market region enters a specialisation during the respective periods under analysis and 0 otherwise. Covariates refer to the starting year of the corresponding period. *** indicate significance at the 1% level, ** significance at the 5% level, * significance at the 10% level. Heteroscedasticity -robust standard errors clustered at the region-occupation level are reported.

Table 6-2. The entry of occupational specialisations in German labour market regions.

6.9 Does relatedness fosters entries into skills intensive occupations?

This section considers the question whether relatedness is of crucial importance for entries into human capital intensive occupations. This is addressed in two different ways. First the sample is restricted to occupations with a human capital intensity larger than 0.5. This implies that the results of models 1 to 3 in Table 6-3 only include those occupations where at least 50 % of the individuals working in this occupation hold a university degree. Similar to above, the coefficient for relatedness remains positive and significant in all three specifications although he is losing some significance in the full model. In comparison to section above, the magnitude of the effect for relatedness increases when the focus is on human capital intensive occupations. Considering the coefficients of the full model in Table 6-3 (column 3), an increase in relatedness at around a given human capital intensive occupation *j* by 10 % increases the probability of entry of this occupation by about 8.5 %.

Dependent variable is $Entry_t$	Model 1 – Relatedness	Model 2 – Full model without fixed effects	Model 3 – F.E.-Model	Model 4 – F.E.-Model with interaction term
Relatedness	0.507***	0.454***	0.179*	0.098***
	(0.041)	(0.054)	(0.109)	(0.033)
class_hc*relatedness				0.198**
				(0.010)
class_hc				-0.048**
				(0.023)
employment_all		-0.002	-0.008	-0.009
		(0.004)	(0.044)	(0.014)
hc_region		0.149*	0.019	0.065
		(0.077)	(0.405)	(0.092)
specialisation		0.006	0.084	0.148***
		(0.038)	(0.151)	(0.038)
share20		0.021	0.043	0.202***
		(0.041)	(0.142)	(0.049)
ln_occ		-0.011***	-0.009	0.014***
		(0.002)	(0.008)	(0.003)
Constant	-0.069***	0.060	0.110	-0.140
	(0.009)	(0.053)	(0.485)	(0.166)
N	18,535	16,127	16,127	145,931
R^2	0.016	0.017	0.010	0.001
Period fixed effects	No	No	Yes	Yes
Region-occupation fixed effects	No	No	Yes	Yes

Table 6-3. The entry of human capital intensive occupational specialisations in German labour market regions. Source: Author's own calculation. Notes: The dependent variable is entry = 1 of an occupation at the German labour market region enters an occupational specialisation during the respective periods under analysis and 0 otherwise. Covariates refer to the starting year of the corresponding period. *** indicate significance at the 1% level, ** significance at the 5% level, * significance at the 10% level. Heteroscedasticity -robust standard errors clustered at the region-occupation level are reported.

A second way to address the question whether relatedness has an effect of entry into human capital intensive occupations is carried out in Model 4. Here, similar to above, a dummy variable is created that is 1 if an occupation *j*'s human capital intensity is larger than 0.5 (*class_hc*). This variable is interacted with the relatedness indicator (*class_hc*relatedness*) to check whether there is an additional effect for human capital intensive occupations. Model 4 in Table 6-3 presents the results. While the coefficient for relatedness remains positive and significant in this specification, there is an additional surplus when relatedness is interacted with the human capital dummy variable. Given this, relatedness increases the probability of entries into human capital intensive occupations by about 20%. These findings further have to be set in the light of the effect of the regional stock of human capital measured by educational attainment (*hc_region*). While first, human capital has the expected positive and significant effect on entry in the model without fixed effects, the coefficient becomes insignificant in the full model while relatedness still positively affects entry. Hence, occupational relatedness is drives human capital accumulation beyond education.

6.10 Robustness analysis

The third part of the analysis presents several robustness checks. They can be differentiated into three different categories. The first five models address different types of outliers that may drive the results by skipping the top 10 percent of region-occupation pairs with the highest relatedness (Model 1 in Table 6-4), the top 10 percent of the regions that have shown the highest number of entries into new sets of occupational specialisations (Model 2 in Table 6-4) as well as the top 10 percent of occupations that have become specialised most frequently (Model 3 in Table 6-4). None of the robustness checks shows different results compared to the baseline scenario in Table 6-2. All specification present a positive and significant effect of relatedness on entry. Regarding the magnitude of the effects, the exclusion of the top regions lowers the probability of entry to 4.3 %, the other two specifications present results that are comparable in size to those presented in Table 6-2. Two additional robustness checks directly address potential weaknesses which arise with the use of location quotients. Model 4 excludes smaller occupations (< than 1000 employees) to avoid that entries and exits are driven by the size of an occupation. Model 5 makes use of an alternative threshold to define entries, exits and the respective comparison groups based upon the location quotient (0.6 instead of 0.5). The results remain largely unaffected by these changes.

Models 6 and 7 split the sample into East and West German labour market regions to check whether different transition histories contribute to differences in the relevance of occupational relatedness on entry into new occupational specialisation. Both East and West German labour market regions are characterised by positive and significant effects of relatedness on entry. Interestingly, the magnitude of the effect is higher for West Germany. Here, an increase in relatedness around an occupation *j* by 10 % increases the probability of entry of this occupation by about 8.1 %. In East Germany the probability of entry remains lower at about 6.5 %.[39]

[39] Robustness checks show that this differences is mainly driven by the first period under analysis. In the recent periods East German regions behave more similar compared to their West German counterparts.

Dependent variable is $Entry_t$	Outlier analysis					East vs. West Germany		GLM specifications	
	Model 1 - Outlier w/o top relatedness	Model 2 - Outlier w/o top regions	Model 3 - Outlier w/o top occupations	Model 4 - Outlier w/o occupations with less than 1000 employees	Model 5 - Using different LQ values (0.6)	Model 6 - West German regions	Model 7 - East German regions	Model 8 - Probit regression	Model 9 - Logit regression
Relatedness	0.116*** (0.033)	0.080** (0.033)	0.104*** (0.030)	0.109*** (0.033)	0.121*** (0.032)	0.150*** (0.034)	0.176* (0.092)	0.265*** (0.015)	0.267*** (0.015)
N	136,114	134,918	130,895	138,823	145,931	126,121	19,810	145,931	145,931
R^2/Pseudo R^2	0.012	0.013	0.012	0.014	0.012	0.013	0.012	0.021	0.021
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupational controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No

Table 6-4. Robustness analysis for entry into regional occupational specialisation in German labour market regions. Source: Author's own calculation. Notes: The dependent variable is entry = 1 of an occupation at the German labour market region enters an occupational specialisation during the respective periods under analysis and 0 otherwise. Covariates refer to the starting year of the corresponding period. *** indicate significance at the 1% level, ** significance at the 5% level, * significance at the 10% level. Heteroscedasticity-robust standard errors clustered at the region-occupation level are reported. Models 6 and 7 report marginal effects.

The third approach offers results for alternative econometric specifications. In contrast to the linear probability models used before, the analysis conducted using probit and logit models. Both alternative specifications confirm the results. Relatedness positively affects the entry into new sets of occupational specialisations at the regional level in Germany in the period under analysis. In sum, the robustness checks confirm the results in terms of the sign of the coefficients and significance.

6.11 Does relatedness prevent exits of occupational specialisations in regions?

The focus until now has been on explaining the relationship between relatedness and entry into new sets of occupational specialisations.

Dependent variable is $Exit_t$	Model 1 – Relatedness	Model 2 – F.E.-Model
Relatedness	-0.215***	-0.116*
	(0.041)	(0.062)
ln_employment		-0.056*
		(0.032)
hc_region		-1.502***
		(0.157)
Specialisation		0.325***
		(0.091)
share20		0.547***
		(0.113)
ln_occ		0.047***
		(0.008)
occ_hc		0.053
		(0.085)
Constant	0.196***	0.053
	(0.012)	(0.377)
N	81,988	69,135
R^2	0.002	0.064
Period fixed effects	No	Yes
Region-occupation fixed effects	No	Yes

Table 6-5. The exit of human capital intensive occupational specialisations in German labour market regions. Source: Author's own calculation. Notes: The dependent variable is exit = 1 of an occupation at the German labour market region exits an occupational specialisation during the respective periods under analysis and 0 otherwise. Covariates refer to the starting year of the corresponding period. *** indicate significance at the 1% level, ** significance at the 5% level, * significance at the 10% level. Heteroscedasticity -robust standard errors clustered at the region-occupation level are reported.

However, occupational relatedness should also affect the probability of exits from regional occupational specialisations. Table 6-5 presents the results for this kind of relationship. As expected, the effect of occupational relatedness is negative and significant in both specifications. Considering the most conservative estimates of coefficients in model 2 (Table 6-5, column 2), an increase in relatedness around a given occupation *j* by 10 % decreases the probability of exit of this occupation by about 2.6 %. While the magnitude of this effect is smaller for exits in comparison to entries, occupational relatedness is found to affect the two main elements of the dynamics of the skill composition of regions in Germany.

The set of regional and occupational controls offers additional insights on the drivers of exits from regional occupational specialisations. Similar to the analysis of entries, regional specialisation (*specialisation*) has a positive effect on exit from occupational specialisations as it narrows the focus of regional occupational activities. In addition to that, the share of employees working in firms with less than 20 employees (*share20*) shows a positive effect on exits from occupational specialisations. As before, the analysis confirms that small firms are important drivers behind the dynamics of regional structural change. Lastly, human capital when measured by educational attainment is of crucial importance when explaining exits from regional occupational specialisations. Model 2 shows a negative and significant of this variable. In terms of elasticity, an increase in the share employees in a region holding at least a bachelor degree by 10 % decreases the probability of exits from occupational specialisation by about 8.5 %. Thus, a higher regional stock of human capital contributes to more robust patterns of regional occupational specialisations as it prevents exits of from present set of skills.

6.12 Conclusions

This paper shows that regional human capital dynamics, approximated by rise and fall of occupational specialisations, are driven by the degree of relatedness of regional occupational structures. Analysing the long-term evolution of occupational structures in the manufacturing industry in 270 German labour market regions in the period 1992 to 2010, the results contribute to the understanding of why and how skills accumulate in space. That is, regions move though the occupation space by diversifying into occupational specialisations related to the existing set of the region. Importantly, the effect of occupational relatedness is more pronounced when considering skill-intensive occupations. The results furthermore show that occupational relatedness drives human capital accumulation beyond measures of regional educational attainment. In addition to that, occupational relatedness exert additional influence on exits from occupational specialisations. A high degree of relatedness around a certain occupation decreases the probability of exit of this occupational specialisations from the region.

The results reveal that regions can have limited prospects for skill accumulation because their current set of occupational specialisations may put too many constrains or offer only limited possibilities for future occupational diversification. This may explain why lagging regions, and in the case of Germany especially East German regions, have difficulties in catching up to their West Germany counterparts. Indeed, when comparing the position of East and West Germany as a whole in the occupation space, West Germany is specialised in almost the entire set of (skill-intensive) densely connected core occupations while East Germany occupies the less connected occupations in the periphery. This provides West German regions with more opportunities to enter related skill-intensive occupational specialisations and will also dampen exits levels leading to more robust occupational patterns in West Germany. To the contrary, East German may suffer from constrains with regard to regional human capital accumulation because of being specialised in routine job categories. This may come along with low potentials for upgrading industrial structures to benefit from qualitative regional change (Pyka and Saviotti 2007).

Future research efforts should directly address this spatial dimension of the occupational divide in Germany and assess the implication of occupational relatedness for regional development in East and West Germany. This especially considers the relative importance of relatedness for entries and exits of occupational specialisations in both parts of the country as well as the evolution of the relatedness of regional occupational structures over time. Thereby it is of importance to link the insights on the effects of occupational relatedness to literature on the role of amenities (Shapiro 2006) and educational measures of human capital (Glaeser and Resseger 2010) to assess their relative importance for regional human capital accumulation and for different alternative economic outcomes. This would allow to draw direct conclusion for regional policy alternatives. Also the concept of occupational relatedness is open for future research. Research should address the black box of relatedness and try to directly assess the distinction made between occupational proximity and complementarity to derive further implications that allow to depart from their joint identification. Technical complementarities and knowledge driven occupational interdependencies are both present at the regional level. While Hasan et al. (2015) use detailed job descriptions at the organisational level to identify technical complementarities, the employment patterns of the recent economic crisis could provide valuable insights on how these complementarities shape the occupational relatedness at the regional level. This especially holds for patterns of short-time working used extensively in Germany in the years of the recession in 2008 and 2009.

Appendix A6

	exit	related-ness	ln_em-ployment	hc_region	speciali-sation	share20	ln_occ	occ_hc
exit	1							
relatedness	-0.065	1						
ln_employment	-0.097	0.638	1					
hc_region	-0.003	0.521	0.503	1				
specialisation	-0.053	-0.402	-0.135	-0.418	1			
share20	0.083	-0.172	-0.596	-0.209	-0.427	1		
ln_occ	-0.180	0.009	0.019	0.022	-0.016	-0.015	1	
occ_hc	0.080	0.110	0.123	0.154	-0.029	-0.086	-0.006	1

	entry	related-ness	ln_em-ployment	hc_region	speciali-sation	share20	ln_occ	occ_hc
entry	1							
relatedness	0.060	1						
ln_employment	0.006	0.540	1					
hc_region	0.032	0.454	0.455	1				
specialisation	-0.052	-0.407	-0.045	-0.374	1			
share20	0.028	-0.028	-0.541	-0.145	-0.540	1		
ln_occ	0.009	-0.114	-0.057	-0.043	0.020	0.023	1	
occ_hc	0.017	-0.101	-0.046	-0.031	-0.011	0.040	0.146	1

Appendix A6-1. Correlation matrix for entries and exits.

Chapter 7

Conclusions

7.1 Introduction

The preceding chapters have discussed three different dimensions of relatedness: vertically related variety in terms of input-output linkages, related variety of regional human capital as indicated by the spatial distribution of occupations, and technological relatedness of industries in terms of R&D efforts measured by single and collaborative R&D projects. All of these dimensions are found to be of relevance in Marshall's theory of industry agglomeration: the focus on input-output linkages may indicate savings in transport costs by spatial proximity to input suppliers or final consumers. Occupational co-specialisation in and functional specialisation of regions may contribute to benefits from labour market pooling or thick labour markets. And all three dimensions together may facilitate knowledge spillovers.

These foci present an extension and a more comprehensive analysis of the role of related variety as a source of agglomeration economies and a driver of regional development. So far, the relatedness literature is dominated by a focus on technological relatedness and cognitive proximity with a strong reliance on patent and industry level data (Frenken et al. 2007, Boschma et al. 2009, Boschma and Iammarino 2009, Boschma and Frenken 2011, Boschma et al. 2012, Boschma et al. 2015). This dominance can be regarded as a shortcoming of the relatedness approach. As stated before, in theory, the effects of related variety can be assumed to be present across a wide range of economic agents and their activities. Although the effect of relatedness might thereby differ with respect to magnitude, the EEG stresses that related regional economic evolution should work independently of entity or activity studied and measure employed (Essletzbichler 2015). The increasing evidence on the multi-dimensional nature of relatedness led to the research questions stated in chapter 1. They guide the contribution of this thesis that is to widen the analytical focus of the concept of related variety and to analyse whether related variety shapes regional economic evolution in terms of input-output linkages, the spatial distribution of occupations, and technological relatedness of industries in terms of R&D efforts.

There are two different elements in the research questions raised in chapter 1. First, the multi-dimensional nature of relatedness needs to be addressed with respect to different types of economic agents and activities mentioned above. Second, we need to test for the effects of related variety in these settings on different outcomes related to regional economic development. The next sections will offer a chapter wise discussions on these two elements and summarise the main findings. Section 7.3 shows how the finding of this thesis may be used to inform policy makers on how to cope with structural change from a regional perspective. Section 7.4 will mention some of the limitations of this work. Based upon the insights of all the chapters, section 7.5 will end this thesis by pointing out further research questions that may contribute to a new research agenda on related variety and regional development.

7.2 Discussion of the main findings

Vertically related variety in industrial clusters

Chapter 2 approaches the multi-dimensional nature of relatedness from a twofold perspective. First, the chapter ties into the discussion on industrial clusters. Second, the chapter applies an input-output based method to identify the degree of their localised vertical relatedness in Germany. This approach is in line with the basic empirical operationalisation of the cluster concept. While the definition of Porter (1990) has been criticised because of being vague in several dimensions, two core characteristics of industrial clusters are widely acknowledged in the literature: geographical concentration of economic activity and the existence of linkages between certain actors (Martin and Sunley 2003).

The comprehensive and systematic empirical identification of linkages is difficult. We agree to this point and first, identify basic industrial cluster structures by means of a measure of spatial concentration (Sternberg and Litzenberger 2004). In order to obtain directed information on the degree of their vertical relatedness, the approach transforms value flows of national benchmark input–output tables into binary information by the help of minimal flow analysis (Schnabl 1994). The results present a snapshot of the German cluster structures in the year 2003. In a first step, the district level results show that out of 439 regions, 257 do not host industrial cluster structures according to the proposed selection criteria. 182 regions accommodate at least one industrial cluster in the region. Out of these 182 regions, we identify signs of horizontal clusters with only one concentrated economic sector in 110 regions. In 45 regions, strong horizontal clusters could be detected, in the sense that these regions consist of more than one, however, vertically unrelated industrial clusters. Overall, only 27 regions showed vertically related industrial clusters, indicating that, at this spatial scale, only a small number of regions can create benefit from relatedness in terms of input-output linkages. The spatial allocation furthermore reveals that clusters with vertically related variety can be found in the large urban areas such as Munich, Berlin, Hamburg, Cologne, and Frankfurt, while the south-west of Germany (Baden-Wuerttemberg) and the Ruhr area display many spatially proximate vertically related industrial clusters. East Germany falls short in this context. Only a couple of regions (Leipzig, Dresden, and Rostock as a maritime cluster) have successfully developed industrial clusters while the majority of regions do not show any industrial clusters according to the classification scheme.

Subsequent research using this approach has proven that it offers valuable insights. Brachert et al. (2011) present an extension that allows including related variety among neighbouring regions, a fact that has received little attention so far in the relatedness literature (see Boschma et al. 2016 for a recent contribution). In order to examine whether input-output-based measures result in similar conclusions on the link between related variety and regional development, Kubis, Brachert and Titze (2012) transfer the approach to the analysis of growth effects of different types of industrial clusters in Germany. While unrelated or vertically isolated industrial cluster structures are found to have a negative impact on regional growth in the period 2002 to 2007, positive growth effects can be identified when industrial clusters are characterised by a high degree of vertically related variety. In sum, the findings support the relevance of the concept of related variety on regional development from an input-output perspective.

Related variety in occupations and the role of regional functions

The chapters 3 and 6 contribute to the understanding of how a distinctive occupational perspective may shape the effects of related variety on regional development. The occupational lens presents a complementary view on regional human capital accumulation. So far, the majority of empirical studies on the effects and distribution of regional human capital focus on the level of education of the people. Florida (2002) argues using occupations instead. Following Thompson and Thompson (1985), he states that education measures the available stock of human capital in a region. Contrary, occupations allow analysing what people actually do with their level of education (see also Markusen 2004). Hence, the occupational lens brings up the specific regional skill structure as a potential driver of the spatial distribution of human capital and as an accelerator of the effects of related variety.

The latter aspect is addressed in chapter 3. In their seminal paper, Frenken et al. (2007) were the first to show that a differentiation of Jacob's externalities is needed to understand the effects of related and unrelated variety on regional outcomes such as productivity, unemployment and employment growth. Given this, related variety is supposed to be of relevance, especially for regional employment growth. Subsequent studies found this positive effect to hold not only for the Netherlands but also for other countries such as Italy (Boschma and Iammarino 2009), Spain (Boschma et al. 2012), and with some restrictions for Finland (Hartog et al. 2012) and the UK (Bischop and Gripaios 2010). Chapter 3 is the first paper that discusses the concept of related variety from the perspective of German labour market regions. It confirms the positive relationship between related variety and regional employment growth for German regions in the period 2003 to 2008. In contrast to Frenken et al. (2007) but in line with Firgo and Mayerhofer (2016) for Austria, it also finds unrelated variety to be positively associated with employment growth. Hence, German labour market regions benefit from both dimensions of variety in the period under analysis.

Beyond that, the major contribution of chapter 3 is to address a conceptual issue concerning the definition of relatedness in the traditional approach by Frenken et al. (2007). Wixe and Andersson (2016) argue that in contemporary economies regions tend to specialise in functions rather than in industries (see also Duranton and Puga 2005). This allows deriving the hypothesis that relatedness at the level of individuals and their respective occupation is equally important as relatedness in terms of industries. The occupational perspective allows paying attention to the kinds of work the regional economy does and avoids restricting the analysis to the kinds of products a region makes (Feser 2003). Chapter 3 integrates the occupational dimension in the concept of related variety by a subdivision of the related and unrelated variety indices into three categories of occupational functions, namely *White Collar*, *R&D* and *Blue Collar*, as developed by Bade et al. (2004). We offer results for establishing that conceptual progress can be made when the focus of the analysis goes beyond solely considering industries. The findings suggest that the drivers behind related and unrelated variety differ from an occupational-functional perspective. While the positive effect of related variety is driven by high degrees of relatedness in the regional *R&D* and *White Collar* functions, the effects of unrelated variety are spurred by *Blue Collar* functions. Given that *White Collar* and *R&D* functions are characterised by a non-routine nature and thus offer much more potential for localised knowledge spillovers (Robert-Nicoud 2008), the results indicate that related variety in these functional categories acts as an accelerator for regional development.

Chapter 6 elaborates more on the occupational dimension of related variety. Inspired by empirical findings demonstrating that the distribution of human capital in space is diverging (Glaeser and Berry 2005), the basic argument developed in chapter 6 is that the occupational composition of a region matters for regional skill accumulation via its effect on the entry (exit) of related (unrelated) occupational specialisation. Thereby the current occupational composition places a region in a so-called occupation space, a network representation of occupational interdependencies, which determines future regional diversification possibilities. The focus on regional occupational structures is of importance because occupations reveal a human capital driven way of how people percept, interpret and evaluate knowledge (Markusen 2004). Aggregated to the regional level, the occupational structure may offer potentials but also put constraints on human capital accumulation through its effect on localised human capital externalities.

The empirical results confirm the supposed relationship between regional human capital dynamics and the degree of relatedness of regional occupational structures. Analysing the long-term evolution of occupational structures in the manufacturing industry in 270 German labour market regions in the period 1992 to 2010, the results show that regions move through the occupation space by diversifying into occupational specialisations related to the existing set of the region. Most importantly, the effect of occupational relatedness is more pronounced when considering skill-intensive occupations and robust against the inclusion of alternative measures of regional human capital such as educational attainment. In addition to that, high degrees of relatedness of regional occupational structures are found to reduce the probability of exits related occupational specialisations. Hence, occupational relatedness and regional occupational structures can be seen as driving forces of dynamic skill accumulation of regions.

This occupational perspective is of special relevance for Germany. The chapter closes with the findings that East German regions with their transition history and resulting branch plant economy may have limited prospects for skill accumulation because their current set of occupational specialisations offers only limited possibilities for future occupational diversification. This comes along with low potentials to benefit from qualitative regional change and opens up the concept of related variety to other bodies of literature such as industrial upgrading in (transition) economies (Zenka et al. 2014).

Related variety in (subsidised) R&D projects and its effect on technological change and regional development

The chapters 4 and 5 discuss the concept of related variety from the perspective of a specific economic function, that is firm-level research and development efforts. Originating from studies on recombinant innovation (Fleming 2001), the chapter is to our knowledge the first to develop a firm-project-level foundation of search processes by industries for knowledge over time (see also Janssen 2015 for a more recent contribution). Existing studies so far are restricted to the focus on university-industry relations only (D'Este et al. 2013). Using a unique and comprehensive dataset on publicly subsidised R&D projects for Germany, the chapter contributes to the discussion on related variety by differentiating technological relatedness into the notions of technological similarity and complementarity. Technological similarity is defined as given when firms from different industries contribute independently of each other to the progress within a similar narrow technological domain. This should allow them to create benefits from their mutual absorptive capacity with positive effects on innovation quantity. Contrary, technological complementarity is defined empirically by the co-occurrence of two industries in a joint R&D collaboration project. It follows the argument that organisations' resources must fit for enabling collective learning and innovation. Consequently, we use this co-occurrence of firms in collaborative R&D projects to assess the inter-sectoral technological complementarity. The distinction between similarity and complementarity is of importance because both dimensions have different consequences for the bridging of technological distances between industries and are supposed to affect the outcomes of innovations efforts (Makri et al. 2010).

Chapter 4 addresses inter-industrial technological complementarity. It is argued to be one crucial element for effective R&D collaboration. The real structure of inter-industry complementarity is, however, still largely unknown. Based on the argument that organisations' knowledge resources must fit for enabling collective learning and innovation, the chapter uses sectoral information about the co-occurrence of firms in collaborative R&D projects in Germany to assess inter-industry technological complementarity between 129 sectors. The results are mapped as complementarity space for the Germany economy for the period from 1990 to 2011. The results illustrate dynamic inter-sectoral relationships of technological complementarities both from a dyadic and portfolio/network perspective. This latter is important, as complementarities may only become fully effective when integrated into a complete set of different knowledge resources from multiple sectors. The dynamic perspective reveals shifting demands for knowledge resources among sectors at different time periods. The example of ICT and ICT services further show how the evolution of a new technology produces different patterns of inter-sectoral knowledge integration potentials over time.

Chapter 5 abstracts from the pure industry level analysis and approaches the role of similarities in industries technological profiles and their effects on regional innovation. The chapter again applies data from the comprehensive dataset on publicly subsidised R&D projects for Germany. The chapter adds to the relatedness literature by arguing that the effects of R&D subsidies go beyond the extension of organisations' monetary resources invested into R&D. This particularly concerns the type of knowledge resources shared in research collaborations. Hence, subsidised R&D collaboration will be particularly beneficial when partners with related knowledge come together (Breschi et al. 2003). While Fornahl et al. (2011) provide some evidence for this argument at the firm-level, chapter 5 extends the argument to the regional level. To approximate the degree of technological similarities between two organisations, this chapter makes use of their industrial classification and establishes an index on the basis of information on individual R&D subsidisation grants. In contrast to the complementarity dimension, this means that only subsidised projects conducted by a single organisation are considered. R&D subsidisation projects are classified in the database by a technological focus, which is represented in the subsidies data' technological classification scheme. It is argued that industries are more similar, the more frequently firms obtain (individual) grants classified into the same technological class.

Furthermore, the results show that supporting interregional R&D collaboration generally does not facilitate regions' innovation growth. However, when controlling for similarity, a positive significant coefficient is obtained for interregional collaboration. This meets the idea of related variety. Some degree of similarity is necessary to allow for efficient communication and ensure complementary resources. However, the higher the degree of partner resource similarity in subsidised R&D collaboration, the more likely are combinations of redundant knowledge resources. Put differently, similar knowledge resources imply that firms share similar cognition, perceptions, interpretations and evaluations. The innovative potential for novel resource (re-)combination is reduced in collaborative projects involving too similar knowledge resources.

Taken together, the findings indicate that relatedness has a multi-dimensional nature and that the relatedness patterns shape the dynamics of regions and technologies. As a consequence, the proposed occupation or similarity/complementarity space can provide valuable insights for the study of (regional) economic development and contribute to the understanding how related regional economic evolution works.

7.3 Implications for policy

Regional or better to say place-based policies are an integral part of the policy mix in many countries. In the United States, approximately 95 billion $ per year has been spent on place-based policies since the first decade of the 21st century (Kline and Moretti 2014a). The same holds true for the European Union (EU). Here, a significant fraction of the EU fiscal budget is handed out to member states via the Structural Funds to support lagging regions. In the 2007-2013 programming period, expenditures amounted to 278 billion € (i.e. 39.7 billion € per annum, or 28% of the EU budget) (Ciani and de Blasio 2015).

The main goals of these policy measures are to increase employment and productivity, particularly in disadvantaged areas and to assist regions to better cope with and foster structural change. Thereby, place-based policies comprise a variety of measures, ranging from those that focus on enterprise zones (Neumark and Kolko 2010), cluster policies (Falck et al. 2010), smart specialisation strategies (Foray and Goenaga 2013) or even large-scale regional development programs (Kline and Moretti 2014b). From an economic theory perspective, it remains questionable whether these policies work in the way they were originally intended (Glaeser and Gottlieb 2008). On one hand, the presence of market failures with a spatial dimension may justify intervention. Hausmann and Rodrik (2003) argue that market failures may prevent regional structural change because entrepreneurial discovery might be hindered by spillovers and imitation by others. Moretti (2010) and Neumark and Simpson (2014) furthermore find agglomeration economies, spatial mismatch, network effects, or equity motivations as potential rationales that justify place-based policy schemes. On the other hand, the literature discusses the drawbacks of such interventions, all of which lead to non-productive factor allocations.

The goal of this thesis was not to present econometric evaluation studies that allow for the identification of (causal) effects of concrete policy measures. This is for sure an important field for future research because it can help clarify if and how place-based policies work. However, this thesis may inform policy makers in a way that the chapters 2, 3 and 6 point towards sources of market failures that may justify policy measures and highlight the role of related variety in this context. This first concerns the design of cluster policies with a special focus on vertical relatedness in terms of input-output linkages. Both aspects can be related to the presence of agglomeration economies. Industry localisation and knowledge spillovers may actually create benefits from the presence of workers in related industries. Hence, policy makers should be aware of different types of industrial clusters both from a spatial and inter-industry perspective. Thereby the approach developed in chapter 3 may help to underscore the perspective toward a 'one size fits one' cluster policy (Crespo et al. 2015). Furthermore, it may help policy in the identification of the regional absorptive capacity for cluster policies and potential effects on the allocation of productions factors towards economically leading regions. Given this, the identification of the presence of vertically related variety is of relevance because it is found to contribute to faster growth of industrial clusters at least in the German case (Kubis et al. 2012).

The same argument of agglomeration economies holds for the distinctive occupational dimension on relatedness developed in the chapters 3 and 6. Moretti (2010) highlights the role of thick labour markets as source of agglomeration economies. Occupational relatedness as well as related variety in occupational functions may serve as indication for presence of thick markets contributing to better worker-firm matches and provide insurance against local demand shocks. The thick labour market argument can also be extended to markets for intermediate inputs, especially those that are specialised and non-tradable such as computer programming or legal support (Neumark and Simpson 2014). This argument by Moretti (2010) is again very much in line with the idea of the occupation space that may serve as source of information for policy makers on possibilities (in this case especially West German regions) and limitations (here especially for East German regions) of future diversifications in terms of benefits from thick labour markets.

In addition to that, the occupational perspective offers politicians more specific insights into the sources of knowledge spillovers than agglomeration economies per se. This is because knowledge is more likely to spill over from more highly-educated workers due to the knowledge they possess and the work they do (Neumark and Simpson 2014). Hence, the occupation space can provide rationales for local government to try to generate or attract skilled workers – e.g., through creating or supporting educational institutions, in particular, universities. Thereby, the potential for local knowledge spillovers can serve as a rationale for place-based policies.

But again, while findings of the thesis point towards sources of market failures that may justify place-based policies, this thesis has not investigated the effect of policy measures as such. It is still to be shown how and to what extent how relatedness has a (causal) effect when being part of place-based public policies for instance in investment grants that subsidise diversification efforts of firms such as the Joint Task for 'Improving the Regional Economic Structure' (GRW) in Germany.

Beyond place-based policies, chapters 4 and 5 offer insights into the role of relatedness in innovation and technology policy. Especially chapter 5 has analysed a whole bundle of innovations policies issued by different federal agencies in Germany. While the study cannot say anything about the effects of specific policy measures, it shows that subsidies for collaborative R&D do impact regional R&D activities. However, the effect strongly depends upon whether collaboration connects the right combination of organisations. Hence, the degree of relatedness in partner choice is brought into the context of R&D subsidisation and consequently should become a central concern of R&D policy. The study shows that inter-regional R&D collaborations characterised by technological relatedness are most valuable for regional innovation. Second, chapter 5 furthermore puts forward that subsidised collaboration can help organisations to become embedded into (subsidised) inter-organisational R&D collaboration networks. This may allow regions to gain access to knowledge diffusing in these networks. Hence, policy makers should be aware of these effects because traditional evaluation approaches at the firm-level are likely to miss these network effects. This calls for complementary evaluation approaches on aggregated (system) levels.

7.4 Limitations

Until now, we discussed the contributions of this thesis to the relatedness and economic geography literature. However, there remain open questions and it is also necessary to point out some limitations of this work.

A first general limitation comes from the fact that this thesis addresses the concept of related variety from the perspective of one single country, that is Germany. This implies that the chapters do not deal with a random dataset of many regions from different countries. While this makes the thesis coherent in a spatial sense, the question remains whether the findings can be replicated or subject to policy implications elsewhere. This especially holds with respect to the implications of this work for developing economies. While here, a differentiation of the results by the Eastern and Western part of Germany can provide interesting insights for developing countries into aspects such the functional specialisation of regions, East Germany is still a comparatively developed region. In addition to that, the single country focus on a developed nation may underscore the role of institutions in (regional) economic development. Institutions have not been the focus in the thesis. However, I will outline how the institutional dimension and especially institutional differences between East and West German regions can be used to analyse the effects of institutional variation on related variety and regional development.

Regarding the chapters, the most prevalent limitation in chapter 2 arises from the strong assumption that national benchmark value chain also holds at the regional level. What an input-output perspective can do, is to map inter-industry flows of intermediate goods from an aggregated perspective. Detailed data in a more fine-graded sectoral (like the benchmark value chains in the United States) or regional (at the level of federal states or even lower levels such as labour market regions) classification remain inaccessible due to data restrictions. This makes the assumption mentioned above necessary, given the knowledge that regions are not usually characterised by the same production structures as the national average. However, this assumption is quite common to make in the literature (Feser 2005). Thereby it seems to be of crucial relevance to consider regional input-output linkages because they are found to be the most important factor explaining industrial co-agglomeration (Ellison et al. 2010). Second, it is supposed that productivity is equal in all German districts in an industrial sector, allowing one to portion the intermediate inputs to the districts according to its regional share of employment in the relevant industrial sector. Hence, detailed regional industrial information on productivity and inter-industry linkages could help to improve the analysis but is again not yet available in a systematic and regionally representative detail. Furthermore, the simple focus on input-output linkages might be extended to incorporate innovation flows. This means that the importance of interdependencies between cluster structures can also be viewed in relation to R&D efforts and product-embodied R&D flows (Drejer 2003). One way to deal with this issue is the recalculation of input–output coefficients and the introduction of knowledge within the input–output concept.

In chapter 3, some limitations are of a more technical nature and apply to the use of SIC-based measures to determine the degree of related and unrelated variety. The rationale for applying standard industrial systems (SIC) to measure relatedness rests on the assumption that two economic entities sharing the same SIC code show commonalities in terms of input requirements, production functions or technological issues. However, the application of SIC-based measures also results in various shortcomings. Varying degrees of breadth in SIC classes can produce artificially high (low) numbers of relatedness as a result of more fine (coarse) graded classification breakdowns. Furthermore, approaches using SIC classifications implicitly assume equal dissimilarity between different SIC classes and relatedness within a SIC class. They are affected by classification errors and exclude cases in which two industries are dynamically related. Tanriverdi and Venkatamaran (2005) additionally point out that SIC-based measures do not allow insights into the types of the underlying relatedness as the effects can arise from different kinds of functional resources, a fact that might be of special relevance when using standard industrial classifications.

A further limitation of the chapters 3 and 6 rests in the restriction of the analysis to the manufacturing sector. This means that both chapters do not consider service industries as well as the interplay of the manufacturing and service sector at the regional level (see for example the work on skill-relatedness by Neffke and Henning (2013) who consider these interactions). Therefore, it remains unclear, whether these findings have similar implications for the service sector. In addition to that, it also remains worth considering the service sectors also from a theoretical perspective. The discussion on skill-biased technological change presents arguments that favour the expansion of non-routine tasks usually assigned to occupations in R&D or management whereas putting pressure on routine manual tasks usually carried out in production (Autor et al. 2003). It implies that in future, fewer people will be employed in production oriented occupations while employment in production related services (e.g. R&D, technical services, management and organisation related occupations) will expand. This has severe implications for both the occupational structure within manufacturing and for the demand of services in space and could therefore be an important field of future research.

Regarding the chapter 4 and 5, limitations arise from the application of the database on publicly subsidised R&D projects in Germany. The first issue concerns the external validity of the data and hence the results. The database might be subject to political bias as the underlying R&D projects only include publicly subsidised R&D collaboration projects issued by federal ministries. This neglects a second important source of R&D subsidies, the lower administrative level of the Laender (see Titze et al. 2013, Titze 2014). Next to that, the accuracy of the findings is limited to the degree and extent subsidised R&D projects reflect actual collaboration patterns. Furthermore, the chapter focuses on collaboration among German organisations and do not incorporate insights from international collaboration patterns. However, this could be integrated to some extent by widening the database to projects published in the EU CORDIS database including information about collaborative R&D in the EU Framework Programmes. Also, a comparison to patent-based alternatives may correspond to a more detailed analysis of the similarities and differences between inter-industry structures of innovation input (firm-level R&D projects) and output (patents).

One further limitation considers the direction of causality between the proposed relationship between different dimensions of relatedness in this thesis and the respective outcomes at the level of industries and regions. The question remains whether relatedness causes regions to create more employment or gross value added or to be more innovative or, the other way around, whether high growth regions cause higher levels of relatedness. Chapter 5 has addressed causality issues to some extent by applying a Heckman selection model. However, the presence of endogeneity issues might produce some biases in the other estimations of this thesis. It remains therefore of crucial relevance for further research to develop identification strategies that allow testing for causal effects of patterns of relatedness on specific outcomes in the sense of models proposed by Angrist and Pischke (2009).

7.5 Future research

The section above already mentioned some avenues for future research especially with respect to the shortcomings of each of the chapters in this thesis. This last section will discuss broader topics in the economic geography literature whereas insights from this thesis can tie in and contribute to more comprehensive insights in the respective fields.

Connecting the multiple dimension of relatedness in time, space and comparative settings

When emphasising the multi-dimensional nature of relatedness, a number of future research questions emerge. In a first step, when finding increasing evidence that related regional economic evolution works independently of entity or activity studied and measures employed, it becomes an important exercise to connect and compare the contributions of the different dimension of relatedness in economic settings.

It seems plausible that different dimensions of relatedness are not independent of each other. In particular, a temporal relationship appears to be very likely. Similar to recent advances in the proximity framework with a shift to a dynamic theory of proximity (Balland et al. 2015), it is important to note that a dynamic theory of relatedness is still needed. When time plays a crucial role in co-evolution of different dimensions of relatedness one might follow the Padgett and Powell (2012, p. 3) statement that ‘in the short run, actors create relations; in the long run, relations create actor’. Reframing this statement with respect to relatedness would lead to the identification of short term patterns of relatedness. Meanwhile, in the long-run relatedness could contribute to the generation of new actors. A complementary industry life cycle perspective might be helpful in this context. Consider the examples of e-mobility and advanced driver assistance systems in the automotive industry. Both aspects have severe implications for the technological relatedness of the automotive industry in favour of shifts of (collaborative) R&D efforts towards battery technologies and electronics that go beyond the former focus construction and engineering. Given the increase in the electronics and software content in cars, firms in the automotive industry are forced to collaborate with new suppliers and experts outside the traditional auto industry such as hardware and software companies. This seems even more important when considering that electronics systems continue to contribute to the majority of innovations and new features in areas such as quality and safety or infotainment. Hence, both technological relatedness in R&D and vertical relatedness in input-output relations are subject to a transformation under this paradigm shift. In addition to that, the technological shift might also contribute to the creation and growth of new actors that especially reflect this pattern of relatedness such as Tesla.

In a similar vein, these developments are likely to change patterns of skill-relatedness (e.g. reflected by inter-industry labour flows in the sense of Neffke and Henning 2013). To stay in line with the example above, this first concerns the changing demands of the automotive industry for skilled labour, especially from the IT industry. However, the changing demand for knowledge is also likely to become part of the set of competences of production workers and might result in the modernisation or the set up new forms of occupational training schemes. Given this, a temporal perspective on diverse but interdependent relatedness patterns can contribute to a better understanding of the shifts in innovations practice. Furthermore, it may help to address priority setting in actions on different dimensions of relatedness from a policy perspective. Herein, it would be interesting to see if and how the design of support programs and chosen technological priorities affect the timely patterns of relatedness. This has so far not been studied in the literature and can be seen as a starting point for the policy recommendations promoting technologies or supporting networks and between certain actors and industries.

Besides a timely interdependence also a spatial interdependence of multiple dimensions of relatedness is of relevance for future research. The production of new knowledge and its diffusion are found to have a distinctive spatial dimension (Audretsch and Feldman 1996). When location and geographic space are key factors in explaining the determinants of innovation and technological change, also the patterns of relatedness should reflect this. Hence, the presence of a multitude of dimensions of related variety in space may open the black box of how space affects knowledge production. This may help to examine how different patterns of related variety affect regional economic performance and opens up the important questions of which type of relatedness matters most in given contexts, what can be learned from analysing different combinations of different relatedness measures and what are optimal configurations of relatedness patterns across space. Furthermore, a multi-dimensional perspective on relatedness in space allows to create benefits by avoiding likely overweights in the relationship among actors that are co-located due to unobserved factors as well as reduce noise if they capture multiple indices of for instance the same agglomerative force. A first step here is taken by recent works of Delgado et al. (2016).

Addressing the role of relatedness in transition economies – regional functional specialisation and its implications for relatedness research

Of special relevance in the spatial interplay of multiple dimensions of relatedness might be the nexus of occupations and industries. Many of the chapters in this thesis considered the manufacturing sector in Germany. This sector is seen as the backbone of the German economy and also as anchor of regional economic policy in both the East and West part of the country. However, the last two decades in German manufacturing are characterised by decreasing employment in the sector as a whole. Employment has fallen substantially from 7.2 million in 1999 to 6.3 million in 2010. The in-depth analysis of these figures reveals that not all types of occupations within manufacturing are equally affected by this trend. Eickelpasch (2014) points to a functional restructuring taking place. Fewer people are employed in production oriented occupations while employment in production related services (e.g. R&D, technical services, management and organisation related occupations) has expanded. This shift is likely to continue as for instance processes such as skill biased technological change favour the expansion of non-routine tasks usually assigned to occupations in R&D or management whereas putting pressure on routine manual tasks usually carried out in production (Autor et al. 2003).

While the shift in the skill content of manufacturing jobs in industrialised economies is well elaborated (Spitz-Oener 2006, Dauth 2014), the geographic implications of functional restructuring is a field that remains underexplored. This is of crucial relevance as Duranton and Puga (2005, p. 343) emphasise that in recent times the main dimension along which regions specialise has shifted "from a specialisation by sector to specialisation by function." Hence, the analysis of regional structural change can benefit from taking into account the underlying occupational structures that point towards functional restructuring. So far, most analysis in the relatedness literature focuses on the industry level without considering processes of functional restructuring (King et al. 2010). Given the gradual substitution of low-skilled routine tasks and the complementary effects on high skilled labour in recent technological change (Autor et al. 2003) as well as the regional variation of occupational structures within industries (Brunelle 2013), industries and occupations both become important to regional analysis as their joint presence may produce conflictive or supportive effects on regional development.

Germany might prove herein an interesting example of how the functional specialisation of regions may allow them to create benefits or to suffer from technological change. This is because East Germany is hypothesised to not yet having developed a stable industrial structure with the absence of certain functions and, thus, Germany will display a very heterogeneous distribution of functions across the nation (Audretsch et al. 2011).

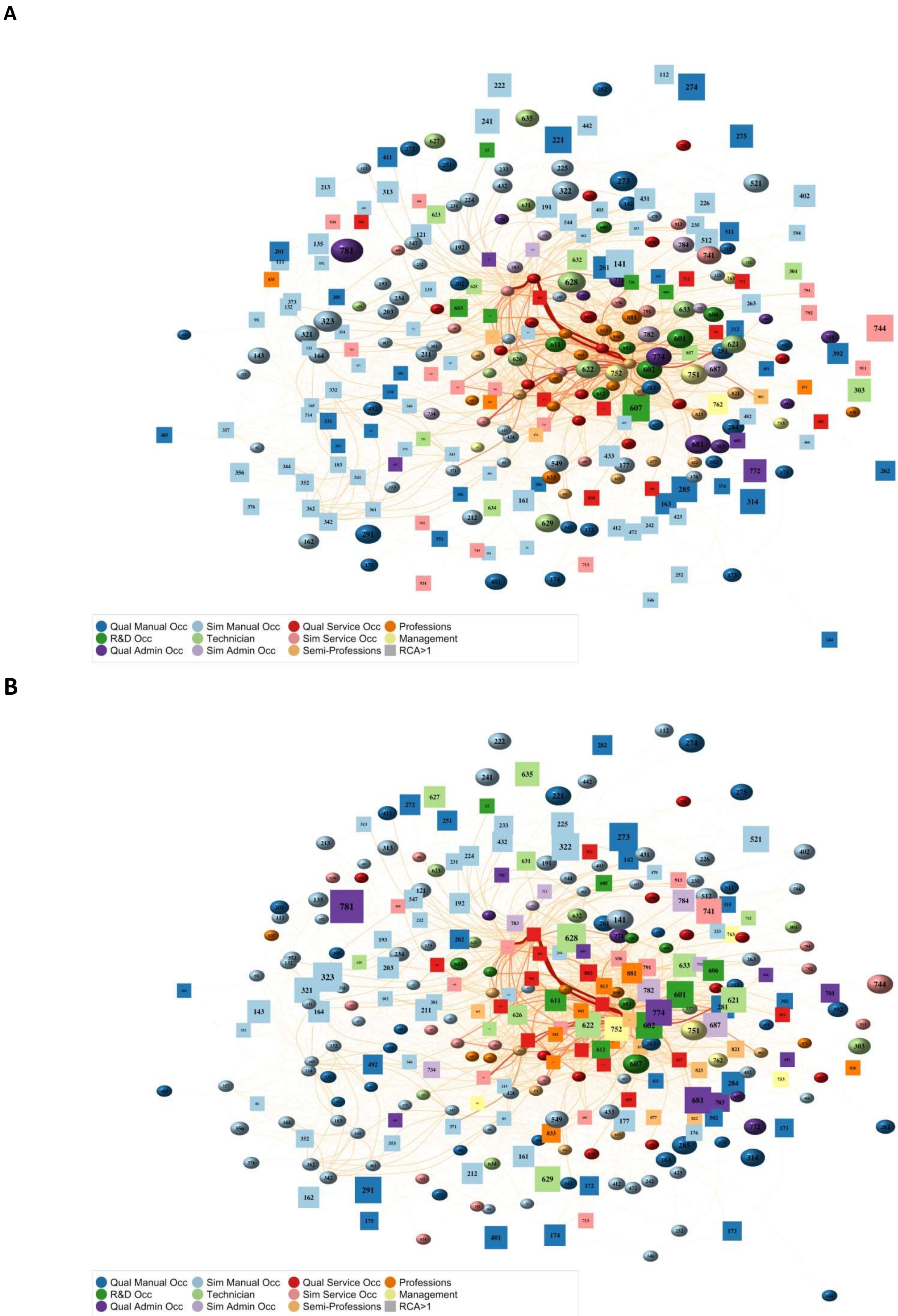


Figure 7-1. The occupation space by region. **(A)** The localisation of East Germany in the occupation space. Occupations with a LQ > 1 are denoted by squares. **(B)** The localisation of West Germany in the occupation space. Berlin is included in this analysis as third region. That this why some occupations remain unspecialised in both illustrations.

Figure 7-1 demonstrates this by holding the occupation space developed in chapter 6 fixed and showing the pattern of occupational specialisations for East and West Germany. The results indicate that East Germany is specialised in occupations being almost exclusively located in the outer occupation space. This part of the space is dominated by simple and qualified manual as well as simple service occupations with on average lower relatedness values. This might cause unfavourable effects in terms of regional resilience when becoming confronted with skill biased technological change and, thus, long-term regional development, and insights that could be of crucial relevance for other post-transition economies that suffer from similar structural weaknesses in terms of lack of regional decision making functions, R&D and headquarter related occupations such as high-quality services.

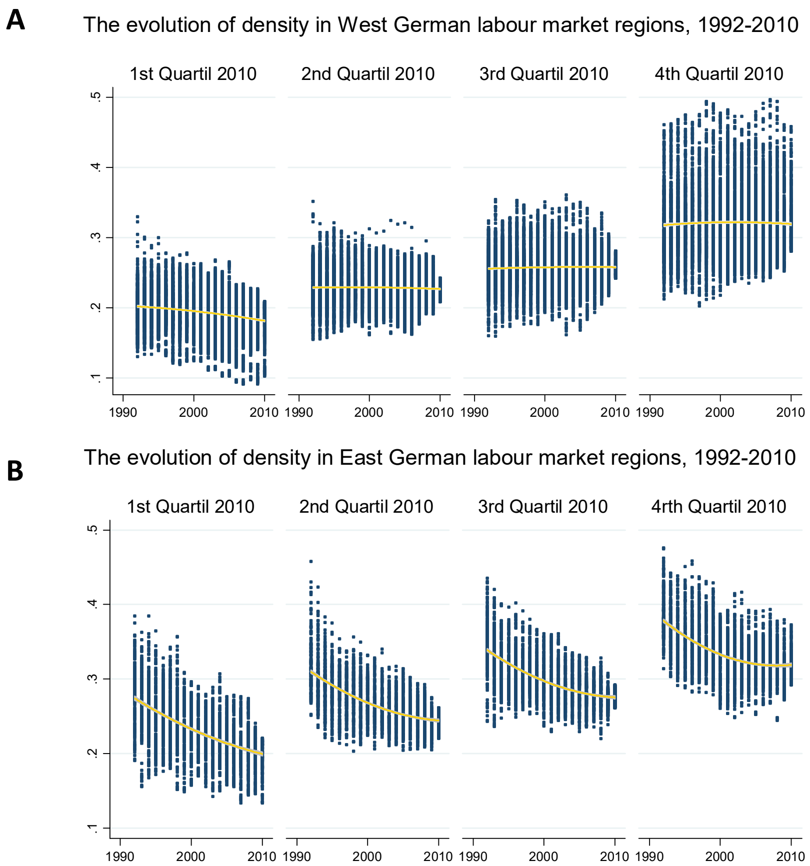


Figure 7-2. The evolution of occupational relatedness for quartiles 2010, 1992-2010. **(A)** West Germany **(B)** East Germany.

Addressing the nexus of occupations and industries might be even more important when analysing the long-term patterns of functional coherence of East German labour market regions. Figure 7-2 adopts a dynamic perspective to show how the entries and exits of occupational specialisation have contributed to changes in the degree of relatedness of German labour market regions between 1992 and 2010. As before, Germany is split into East and West with four quartiles of labour market regions each, regarding their degree of relatedness by occupational functions in 2010. Given this, Figures 7-2 indicates a relatively stable pattern of relatedness across all four quartiles of labour market regions in West Germany. Thus, functional restructuring within manufacturing sector does not appear to contribute to changes in the overall functional specialisation of West German regions. Contrary, East German labour market regions develop differently to their West German counterparts. Although starting at higher mean levels of relatedness across all quartiles, they are characterised by decreasing relatedness values indicating that Eastern German labour market regions are steadily losing functional and occupational coherence. This suggests that entry into and exit from regional sets of occupational specialisations have led shifts in the position of East German regions in the occupation space that are characterised by lower degrees of relatedness thereby limiting future co-specialisation opportunities. Thus, employees in East and West Germany, although maybe working in the same industry within manufacturing today, are likely to perform different tasks with different levels of skills. Further research needs to address the driving forces behind this loss of functional coherence with respect to higher skilled occupation in East Germany. This could provide insights whether the findings for East Germany are generalizable for transitions economies or also for all regions suffering from or being the destination of offshoring activities of large multi-national companies. Thereby, processes of entry in and exit from occupational specialisation and functions might be of crucial relevance in this context.

Related variety and the role of institutions

Another important avenue for future research is the identification of the role of institutions. Although market forces may play a leading role in the process of related diversification, governments both at the national as well as regional level fulfil a crucial role as well. Rodrik (2004, p. 8) highlights that "diversification is unlikely to take place without directed government action". This importance of the public sector can be traced back first to the existence of knowledge externalities leading to underinvestment in R&D following the traditional market failure argument (Fritsch 2014). Second, Hausmann and Rodrik (2003) also highlight the role of coordination externalities. New activities or discoveries need to nurture and may require complementary investments in the surrounding environment. However, they are not necessarily provided by the private sectors itself (Boschma and Gianelle 2014) which implies the need for a co-evolution of institutions, markets and technologies (Nelson 1994).

Given this, Germany might be an ideal case to study the long-term effects of formal institutions on regional development. Because of being subject to (in terms of identification issues spoken) a "natural experiment" with both parts of the country experiencing differences in the economic system (market economy vs. central planning), Germany can be characterised by a set of formal institutions that explicitly address structural weaknesses of East Germany. An interesting example in this case is the most important place-based policy scheme in Germany, the Joint Task for 'Improving the Regional Economic Structure' (GRW). This discretionary investment grant is supposed to reduce the marginal costs of physical capital and addresses the factor allocation of plants. In the 1991–2013 period, 67.7 billion € were spent under this program. A significant share of these expenditures was issued in the aftermath of German reunification since the East German regions, in particular, suffered from a period of deindustrialization. Thereby, one can hypothesise that these capital subsidies helped to transfer pre-existing former GDR production sites into the capitalist system and so favoured the continuation pre-existing development paths. Hence, future research could address the role this place based policy (and e.g. formal institutions) in the context of the relatedness of regional economic structures for low and highly subsidised East Germany regions. This would allow assessing the effect of formal institutions on the continuation of former GDR development paths and put forward the questions of whom should be the target of public policies in the presence of large structural shocks, i.e. people or places.

Second, related economic evolution is also affected by informal institutions (see Cortinovis et al. 2016 for a recent contribution). Informal institutions are usually related to trust and social capital (Putnam 1993). Again East Germany may provide useful insights. A first issue can be seen in the socioeconomic heritage of being exposed to socialism in East Germany. Wyrwich (2013) finds this exposure to deter entrepreneurship in general and (high)-impact entrepreneurship in particular. The socialist regime shaped attitudes which are negatively associated with entrepreneurship (Bauernschuster et al. 2012). Hence, former GDR citizens not only experienced a devaluation of their socialist work experience but also the influence of socialism on mind-set. Given the importance of entrepreneurship in the literature on related regional diversification, it would be of interest to see whether this effect continues to hold (e.g. via intergenerational transmission of entrepreneurial attitudes – see Lindquist 2015) or declines over time and how relatedness of regional economic structures may moderate this effect.

A second aspect of this dimension might be the role of social capital. Chapter 6 and the paragraph above already highlighted the loss of functional coherence as well as a loss of human capital intensive occupations in of East German regions. This fits into a broader picture of East Germany as a shrinking region also in terms of population. From an economic point of view shrinking – particularly shrinking due to outmigration of e.g. occupational functions or population in general – is of relevance for the “returns to social capital”. Social capital is a network good whose value (a)rises if more people join the network and whose value decreases if more and more members leave the network (Bönisch et al. 2013). If social capital is an investment to gain access to community resources (e.g. communities of practice or the creative class in the sense of Florida et al. 2008) then the decline of a community could prevent people from investing in social capital. Therefore, shrinking may have a negative effect on social capital, especially in situations where locally bounded social capital is importance. Hence, the chapter on occupational relatedness in this thesis or the creative class approach by Florida may provide useful complements in the discussion about the returns to social capital in the presence of shrinking or help to develop strategies how to develop locally unbounded social capital based upon patterns of relatedness.

Exploring the black box of related and unrelated variety

A last point of future research relies on the concept of related variety itself. Recent research started to advocate the view that relatedness can benefit from a further differentiation in the dimensions of similar and complementary partner resources (Larsson and Finkelstein 1999, Makri et al. 2010, Neffke 2015, Delgado et al. 2016). However, regarding the definitions of relatedness in the literature, often a clear distinction between similarity and complementarity is missing. As already mentioned above, Makri et al. (2010, p. 605) criticise that: “Relatedness has commonly been defined in broad terms often using similarity and complementarity interchangeably; others have provided incomplete or tautological definitions of complementarity, and a few have ignored it". Given this, an opening of the relatedness concept for instance with respect to technological similarities would allow tracing drivers of learning. This would contribute to a better understanding of the factors that lead individuals and firms to local searches with the aim of the exploitation of what is already known. Contrary, technological complementarities may reflect the combinatory potential of different bodies of knowledge. This conceptualisation may offer insights into drivers that facilitate exploration or experimentation with new sets of knowledge and technologies. Hence, a proper identification of complementarity patterns may contribute to the extent of how complementarities shape the scope of innovations. Beside technological issues, the distinction between similarity and complementarity can also be extended to human capital research by asking which educations can substitute for one another, a fact that points towards similarities. The complementarity dimension can help answering questions of which educations often work together. While these effects have been studied at the regional level to some extent in this thesis, firm-level studies as well as linked-employer-employee data at the regional level may shape our understanding on how combining one input with another increases the marginal returns from that input (Milgrom and Roberts 1995).

In addition to that, the differentiation between similarity and complementarity can contribute to a better understanding of how relatedness in knowledge affects the outcome of interactive learning with respect to innovation quantity, quality, and novelty. Appropriate measures can be related to an actors' innovation productivity or efficiency, to the ability to contribute a 'ripple effect' to stimulate subsequent innovations or the outcomes that reflect the degree to which an actors' portfolio is extended to a broader range of activities that are outside the existing scope and involve some inventive risk. As a consequence, this differentiation fosters our understanding of how relatedness shapes the emergence of capabilities at different levels as actors may assess the gap between their existing capabilities and future targets to decide how to develop these, which also has implications for public policy. It could be hypothesised that similarities in actors' resources contribute to only incremental renewals while complementarities foster more discontinuous developments and points to this two-dimensional nature of relatedness when actors interact (see also Castaldi et al. 2015).

Chapter 8

Summary

8.1 Introduction

The concept of variety can be operationalised from an economics perspective as the number of distinguishable actors, activities and objects required to characterise an economic system (Saviotti 1996). Variety of economic agents is the rule in an economy and of relevance because it is a fundamental component of the long-term development of economic systems. There is increasing evidence on the relationship between the variety of inputs and that of outputs. Furthermore, the economic literature has come up with several direct channels on how variety can be linked to economic development.

This thesis contributes to literature that emerged from the early works of Jane Jacobs (1969). Jacobs highlights the role of industrial variety in cities as sources of new ideas and knowledge spillovers. This spatial perspective laid the ground for variety to enter new (regional) growth theory and also contributed to the emergence of the evolutionary approach in economic geography (EEG). The thesis adopts the EEG perspective.

A crucial concern of this literature is the problem that rests on assumption that knowledge will spill over among a variety of agents simply because they are neighbours (Boschma and Frenken 2009). Contrary, recent literature suggests that proximity between economic actors in various dimensions is needed to foster processes (Boschma 2005). In particular, the notion of cognitive distance has gained attention in subsequent studies. This is because when bringing together economic agents with heterogeneous knowledge, they should be able to bridge knowledge gaps. Put differently, their cognitive distance should by close enough to allow mutual understanding but distant enough to enable innovation (Nooteboom 2000). This cognitive dimension contributed to the introduction of the concept of related and unrelated variety to better understand the effects of variety on the spatialities of novelty (Boschma and Martin 2007).

The basic concern of the EEG is to analyse "*the processes by which the economic landscape – the spatial organization of economic production, distribution and consumption – is transformed over time*." (Boschma and Martin 2007, p. 3). This allows addressing the role of related variety as a force driving regional technological change. Related variety is understood as a result as well as a driver of the direction and pace of future technological change. This means that relatedness in spatial structures and the place-specific features produced so feedback to drive regional economic evolution (Boschma and Lambooy 1999). In theory, economic agents may be related through several channels. In the literature, we find foci on technological relationships in terms of patent or product portfolios, relatedness in skills, scientific fields or even institutional frameworks. These dimensions of relatedness represent an often neglected element of macroeconomic models dealing with general questions of economic growth (Hidalgo et al. 2007). They are addressed in the EEG literature and also in this thesis.

The contribution of this thesis is to widen the focus of the EEG literature. Given that different kind of economic entities and activities require different measures of relatedness, the EEG stresses that related economic evolution should work independently of the entity or activity studied and measure employed (Essletzbichler 2015). So far, the literature on related variety has a strong focus on technological relatedness and cognitive proximity while relying mainly on comprehensive datasets about the spatial distribution of industries, patents or patent citation (Boschma et al. 2015). This thesis will focus on three dimensions of relatedness that not been at the heart of research so far: input-output linkages and vertically related variety, the occupational dimensions of relatedness as well as insights from a project level R&D efforts and their relevance for the analysis of technological relatedness. The second contribution is to address empirical issues related to the question on how to specify the impact of related variety on regional development. First, we contribute to the understanding of how the specific composition and the degree of relatedness of economic agents in space shape their ability to generate variety in terms of entry of new occupational specialisations in regions. Second, we enhance the understanding of how related variety affects different regional outcomes such employment growth and innovation. Third, the thesis offers insights into the structure of inter-industry relations from a technological perspective and explains how the rise of certain technologies shapes inter-industry relatedness patterns.

8.2 Vertically related variety in industrial clusters

The 'cluster theory' has become one of the main concepts promoting regional competitiveness, innovation, and growth. However, there is still a lack of consensus as to what defines a cluster. Most empirical applications focus on measures of concentration of one industrial branch in order to identify regional clusters. The appropriate analysis of industrial linkages is developing in this discussion. The chapter adopted a relatedness perspective on regional industrial clusters structures based upon inter-industry input-output linkages. This perspective is of importance because input-output linkages are found to be a major source of industrial co-agglomeration (Ellison et al. 2010) and a driver of cluster performance in both the short and long run. Thereby, short-run benefits can be a result of the temporal and qualitative availability of key inputs and services with pecuniary advantages arising from the geographical proximity of agents. Long-run benefits are related to the interaction of regional agents (buyers, suppliers and institutions) and their role as source of competitive advantages through innovation, knowledge spillovers and interactive learning.

In the empirical operationalisation, the identification of basic industrial clusters was done by the help of the index of Sternberg and Litzenberger (2004). The chapter then identified vertically related clusters via national input–output tables and the help of minimal flow analysis (MFA). In a first step, a selection of relevant flows was required to create insights into the core structures and the direction of intermediate purchases and sales relations. The regionalisation of the national industry templates was carried out with the allocation of branch-specific production values on regional employment.

As a result, the chapter showed that the presence of vertically related industrial clusters is restricted to only 27 of 439 districts in Germany. This implies that, at this spatial scale, only a small number of regions can create benefits from relatedness in terms of input-output linkages. The spatial allocation reveals that clusters with vertically related variety can be found in the large urban areas such Munich, Berlin, Hamburg, Cologne, and Frankfurt, while the south-west of Germany (Baden-Wuerttemberg) and the Ruhr area display many spatial proximate vertically related industrial clusters. East Germany falls short in this discussion. Only a couple of regions (Leipzig, Dresden, and Rostock as a maritime cluster) have successfully developed industrial clusters while the majority of regions do not show any industrial clusters according to the classification scheme. This points to more a general set of East Germany's structural weaknesses. The chapters 3 and 6 approach more of these aspects.

8.3 Related variety, unrelated variety and regional functions

Chapter 3 provides a conceptual discussion of the way how to identify the effects of related variety. We suggest that individual-level information on occupations can complement the dominant industry perspective in the relatedness literature. Occupations reflect information on skills that point towards the function a region performs in the production process. An 'occupational-functional' hence identifies what specific types of human capital a region possesses, thus is directing attention to the kinds of work the regional economy does.

An 'occupational-functional approach' is able to contribute to the concept of related variety in two ways. First, this allows addressing the functional relatedness of industries in a region (Trippl 2010). When functions within same industry are different for different geographies, these are likely to affect the nature and existence of localised knowledge spillovers. A strong functional asymmetry can be seen as a factor limiting opportunities for effective communication and mutual exchange of knowledge. When the functional relatedness is small, knowledge does not flow easily. A second contribution of an occupational perspective can found in the literature on the functional specialisation of regions. This strand of literature argues that the functional specialisation of regions leads to spatial differences in knowledge spillovers because headquarter functions and R&D departments show a strong affinity to locate next to each other. Hence, differences in the relative importance of regional functions may contribute to differences in the content of tacit vs. codified information in regional transactions and thus the amount of localised knowledge spillovers.

In the chapter we first address the role of related variety on regional employment growth in Germany in the light of the seminal approach outlined in Frenken et al. (2007). Frenken et al. (2007) apply an entropy grounded measure of related variety that relies on the SIC classification. When replicating this approach we confirm that related variety has a positive effect on regional employment growth in the German manufacturing sector in the period 2003 to 2008. However, as stated above, we move on step ahead and argue that sole reliance of related variety on the SIC classifications remains debatable. Conceptual progress can be made by the industrial-functional approach. The approach outlined in the chapter distinguishes three types of occupational-functional groups: *White Collar*, *Blue Collar* and *R&D* workers.

The empirical relevance of the main arguments is tested by a spatial panel approach (Elhorst 2003) that takes into account a spatial lag of the dependent variable and spatial autoregressive disturbances. We show that for regional employment growth, the industrial-functional approach to related variety is of crucial importance. The results support the conceptual discussion put forward. The positive effects of related variety are found to hold especially for *While Collar* and *R&D* functions. This might be a result of the potential for knowledge spillovers that is larger in non-routine activities present in these functional categories. Contrary, the effects of unrelated variety are spurred by *Blue Collar* functions in this period.

8.4 Technological complementarity in inter-industry R&D collaborations

Modern knowledge production requires bringing together different experts. This is because products have become increasingly complex from a technological perspective. However, the notion of expert indicates that also human capital has become more specific. As a consequence, increasing complexity leads to strong interdependencies among experts in knowledge production. Chapter 4 asks the questions - Who are your complements? - from an inter-industry perspective. It argues that given these interdependencies, collaboration patterns of firms may reflect the complementarity patters among industries. It applies a novel comprehensive dataset including firm-level information on subsidised R&D projects in Germany. The chapter claims that this database can be used as an alternative source for measuring technological relatedness of industries from an input perspective that goes beyond the predominantly applied output information on patents or patent citation.

By adopting a complementarity perspective the chapter also contributes to the theoretical discussion of the concept of relatedness. Makri et al. (2010) highlight that the concept of relatedness can benefit from a differentiation into the dimensions of similarity and complementarity (Makri et al. 2010). These two dimensions are intended to shape the quality and quantity of collaboration outcomes of economic agents. Based on the argument that organisations' resources must fit for enabling collective learning and innovation, we use the co-occurrence of firms in collaborative R&D projects to determine the inter-industry technological complementarity between 129 sectors in Germany over a period of more than 20 years. The results are illustrated in a so-called complementarity space for the Germany economy. The space allows insights into industry pair's potential for complementary resource partnering.

The first question of the chapter concerns the role different sectors play in providing complementary resources to others. As expected, the degree centrality highlights here the role of the education sector and that the sectors of research in natural sciences & engineering as well as research in social sciences & humanities (S&H). Sectors with a high betweenness centrality are supposed to operate at the interplay of different groups of sectors holding broker positions. When looking at the betweenness centrality of non-education related sectors, again natural sciences & engineering research takes a central position. This sector seems of particular importance in connecting the education and non-education sphere. The findings further imply that sectors are intensively linked within communities of other sectors but rather weakly connected to sectors belonging to other communities. Hence, the hypothesis of a community-type structure within the complementarity space is confirmed.

In addition to that, the concept of complementarity is seen to be inherently dynamic. The second question we address concerns the changes in attractiveness of sectors' knowledge for other sectors. This is exemplified by the rise of the telecommunication and ICT related sectors over time. The effects of this technological development are particularly visible for degree centrality in the early nineteen-nineties where these two sectors gain massively in centrality. Both sectors are characterised by continuously high degree centrality measures that are contrasted by decreasing betweenness centrality. This suggests that these sectors gain a strong complementarity position within a relatively large group of sectors while at the same time becoming less relevant in the global complementarity space.

8.5 Joint subsidies for R&D, technological similarity and regional innovation

R&D subsidies to organisations are an important tool of innovation policy. This motivates their extensive scientific analysis and evaluation. Chapter 5 adds to this literature by arguing that the effects of subsidies go beyond the extension of organisations' monetary resources. It is argued that collaboration induced by subsidised R&D projects yield significant effects that are missed in traditional analyses. The chapter puts forward the existence of at least two effects that go beyond the boundaries of a single organisation and that need to be addressed in this discussion.

The first effect concerns a collaboration effect. Because organisations interact with their local surroundings, organisational level effects emerging from collaborative R&D subsidies are likely to translate to the regional level. However, the potential benefits might be conditional on the type of resources collaboration partner bring into the projects. In particular combinations of related knowledge are supposed to be of crucial relevance at both the organisational and regional level. The second effect emerges as a consequence of subsidised collaboration projects and represents a network effect. R&D collaborations influence the embeddedness of organisations into territorial innovation systems and access to knowledge diffusing therein. We claim that firm-level evaluation approaches should be complemented by studies on the regional level.

The empirical study on the level of German labour market regions substantiates this claim. The analysis considers the development of German regions' innovation growth between 1999-2003 and 2004-2008. As we are searching for effects on regional innovation quantity, we address the question of relatedness from a similarity perspective and ask the question – What industries contribute similarity to technological change? The measure of inter-industry technological similarity is calculated on the basis of information on individual R&D projects. That is, only subsidised projects executed by a single organisation are considered for the development of the indicator. The basic idea behind the measure is that most R&D subsidisation programs have a clear technological focus which is represented in the technological classification scheme. We argued that two industries' R&D resources are similar the more frequently they contribute (individual) to the technological progress in a narrow technological domain.

The results demonstrate that subsidies for collaborative R&D do impact regional R&D activities. Second, the effectiveness of R&D subsidies for collaborative R&D projects strongly depends on the right combination of organisations teaming up. Herein, providing access to related variety has a positive effect on a regions innovation growth. These results bring partner choice into the debate of R&D subsidisation and consequently should become a central element of R&D policy. The chapter moreover shows that centrality in subsidised inter-regional R&D collaboration networks gives access to valuable knowledge spillovers. This points to strong indirect effects related to the subsidisation of joint R&D projects that are rarely considered in the existing literature. Given the strong relevance of territorial innovation policies in subsidisation schemes, this particularly concerns the regional level.

8.6 A relatedness perspective on the rise and fall of occupational specialisations in Germany

Chapter 3 already stressed that regional economic development needs know-how. Know-how resides in individuals that are experts in their field. Given the former division of labour in the economic sphere, each profession/occupation was supposed to make something. This has changed dramatically with the increasing complexity of modern products. Today's division of labour implies that a multitude of experts is required to create products. Hence, as complexity increases, variety in how-how has to increases as well.

There are different ways to coordinate the generation of knowledge. One dominant way might be the coordination within a firm (Neffke 2015). An alternative form of coordination is reflected by the presence of inter-organisational linkages in space. Herein, space matters via the role of larger cities or regions in providing markets with a greater human capital or occupational variety (Muneepeerakul et al. 2013). Hence, regions may serve as coordination platform for repeated interaction. Indeed, recent literature shows that regional skill accumulation is driven by the interplay of people holding different skill-intensive occupations (Florida et al. 2008).

The chapter explores whether regions are an effective body for coordinating the expertise of different workers given their variety of occupations. It is done by adopting a relatedness perspective based upon patterns of regional occupational co-specialisation. The occupational composition of a region is supposed to matter for dynamic regional skill accumulation via its effect on the entry (exit) of related (unrelated) occupational specialisation. This hypothesis is answered by using information about the spatial distribution of the universe of employees subject to social security contributions in the German manufacturing sector in the period 1992 to 2010. The calculation of occupational relatedness follows Muneepeerakul et al. (2013).

Using linear probability models the chapter finds that the probability of entry into new occupational specialisations in a region increases by 6 percent if the level of relatedness around this occupation increases by 10 percent. This effect is even more pronounced when considering human capital intensive occupations. Interestingly, in this specification the effect of occupational relatedness on entry into human capital intensive occupations remains positive and significant while the measure of educational attainment becomes insignificant. The opposite effect of occupational relationships holds for the relationship between relatedness and exits. An increase in relatedness by 10 percent here contributes to a decrease in the probability of exit from occupational specialisations by 3 percent.

8.7 Conclusions

Chapter 7 outlines the main findings of the thesis and present issues for further research that result from both the limitations and new research questions that have emerged during the writing of this work. The main contribution of the thesis was first to address the increasing evidence of the multi-dimensional nature of relatedness and to widen the concept of related variety to aspects of input-output linkages, occupations and R&D projects as main inputs to innovation processes. Second, we aimed to analyse whether the effects of related variety work out in the intended way in these contexts.

Overall, the findings of the thesis confirm the relevance of related variety in contexts. Hence, the results indicate that relatedness has a multi-dimensional nature and that relatedness patterns shape the dynamics of regions and technologies irrespectively of the dimension studies and measure used. As a consequence, the proposed occupation or similarity/complementarity spaces can provide valuable insights for the study of (regional) economic development and contribute to the understanding how related regional economic evolution works.

The concluding chapter also mentions limitations of this work. These can be found in the strong assumption that the national benchmark value chain holds at the regional level in chapter 2. Furthermore, the incorporation of innovation flows can help overcoming the simple focus on input-output linkages in this chapter. In chapter 3, limitations are of a more technical nature and apply to the use of SIC-based measures to determine the degree of related and unrelated variety. Another limitation of the chapters 3 and 6 rests in the restriction of the analysis to the manufacturing sector. Hence, these chapters do not consider service industries as well as the interplay of the manufacturing and service sector that might be of crucial relevance during the recent period of structural change. In chapter 4 and 5 limitations concern the external validity of the results. This is because the application of the database on publicly subsidised R&D projects in Germany might bias the results. One further limitation considers the direction of causality between the proposed relationship between different dimensions of relatedness in this thesis and the respective outcomes at the level of industries and regions. The question remains whether relatedness causes regions to create more employment or gross value added or to be more innovative or, contrariwise, whether high growth regions cause higher levels of relatedness.

These limitations already pointed to future research opportunities. First of all, the results can contribute to the debate about the relationship of different dimensions of relatedness in time and space. In addition to that, future research needs to address the relative importance of different dimensions of relatedness in different economic settings. Given the findings of the multi-dimensional nature of relatedness, of special relevance to the German case seems to be the nexus of industries and occupations the regional level. This perspective points to a tale of two Germanys. Herein, East Germany is shown to not yet having developed a stable industry structure, as compared to West Germany and thus will not display the same degree of occupational relatedness and functional specialisation as experienced in West Germany (Audretsch et al. 2011).

One can hypothesise that this may cause unfavourable effects in terms of regional resilience when becoming confronted with skill biased technological change. Furthermore, the insights could be of crucial relevance for other post-transition economies that suffer from similar structural weaknesses. Further research needs to address the driving forces behind lack and further loss of functional coherence with respect to high skilled occupation in East Germany whereas the processes of entry in and exit from occupational specialisation and functions might be of crucial relevance. A last point of future research relies on the concept of related variety itself. Further research needs to explore the black box of related and unrelated variety. Herein, a further differentiation in the dimensions of similar and complementary as in Larsson and Finkelstein (1999), Makri et al. (2010), Neffke 2015 or Delgado et al. (2016) might provide valuable insights on how to advance the concept of related variety.

Hoofdstuk 9

Samenvatting

Inleiding

Deze dissertatie is een bijdrage aan het verbreden van de focus van de literatuur over gerelateerde variëteit. De literatuur over dit onderwerp heeft zich dusverre sterk gericht op technologische gerelateerdheid en cognitieve proximiteit (Boschma et al. 2015). Deze dissertatie richt zich op drie dimensies van gerelateerdheid die dusverre geen kernpunten vormden in onderzoek: input-outputverbanden en verticaal gerelateerde variëteit, de beroepsmatige dimensies van gerelateerdheid, en inzichten vanuit projectniveau in onderzoeks- en ontwikkelingsactiviteiten en de relevantie ervan voor de analyse van technologische gerelateerdheid. Wij dragen bij aan het verkrijgen van inzicht in de wijze waarop de specifieke compositie en de mate van gerelateerdheid van economische actoren in ruimtelijke zin hun vermogen scheppen om variëteit te genereren met betrekking tot toegang tot nieuwe beroepsspecialisaties in regio's. Wij versterken het inzicht in de wijze waarop gerelateerde variëteit invloed heeft op verschillende regionale uitkomsten zoals groei van de werkgelegenheid en innovatie, wij bieden inzicht in de structuur van inter-industriële relaties vanuit een technologisch perspectief en wij leggen uit op welke wijze de opkomst van bepaalde technologieën inter-industriële gerelateerdheidspatronen scheppen.

Verticaal gerelateerde variëteit in industriële clusters

Hoofdstuk 2 neemt een standpunt in met betrekking tot gerelateerdheid in regionale industriële clusterstructuren op basis van inter-industriële input-outputverbanden. Dit standpunt is van belang omdat input-outputverbanden een belangrijke bron blijken te zijn van industriële co-agglomeratie (Ellison et al. 2010) en een drijvende kracht zijn achter clusterprestaties op zowel de korte als lange termijn. Voor de empirische operationalisering werden de elementaire industriële clusters geïdentificeerd met behulp van de index van Sternberg en Litzenberger (2004). Vervolgens worden In het hoofdstuk de verticaal gerelateerde clusters geïdentificeerd via nationale input-outputtabellen met behulp van minimal flow analysis (MFA). Het resultaat toont dat de aanwezigheid van verticaal gerelateerde industriële clusters in Duitsland beperkt is tot slechts 27 van de 439 districten aldaar. Dit impliceert, op deze ruimtelijke schaal, dat gerelateerdheid op het gebied van input-outputverbanden slechts een klein aantal regio's voordeel oplevert.

Gerelateerde variëteit, niet-gerelateerde variëteit en regionale functies

Hoofdstuk 3 biedt een conceptuele discussie over de manier waarop de effecten van gerelateerde variëteit geïdentificeerd kunnen worden. Wij stellen voor dat beroepeninformatie op individueel niveau het heersende industrieperspectief in de literatuur over gerelateerdheid kan complementeren. Deze 'beroepsmatige/functionele' benadering identificeert dus welke specifieke soorten menselijk kapitaal een regio bevat dus richt de aandacht daarmee op het type werk dat de regionale economie doet. In het hoofdstuk bespreken we eerst de rol van gerelateerde variëteit in de groei van regionale werkgelegenheid in Duitsland met het oog op de rudimentaire benadering beschreven in

Frenken et al. (2007). Met het repliceren van deze benadering bevestigen wij dat gerelateerde variëteit een positief effect heeft op regionale werkgelegenheidsgroei in de Duitse verwerkende industrie. Wij gaan echter een stap verder, en betogen dat het uitsluitend vertrouwen op gerelateerde variëteit van de SIC-classificaties discutabel blijft. Er kan conceptuele vooruitgang worden geboekt door de industriële/functionele benadering. De resultaten ondersteunen de verkondigde conceptuele discussie. De positieve effecten van gerelateerde variëteit blijken in het bijzonder te gelden voor *kantoor- en O & O-* functies. Anderzijds worden de effecten van niet-gerelateerde variëteit aangespoord door *arbeiders*functies.

Technologische complementariteit in inter-industriële O&O-samenwerkingsverbanden

In hoofdstuk 4 beargumenteren wij dat patronen van sectoroverschrijdende samenwerkingsverbanden van bedrijven op het gebied van O & O van invloed kunnen zijn op de complementariteitspatronen tussen bedrijven. Op basis van het argument dat de hulpbronnen van organisaties in staat moeten zijn om collectief leren en innoveren mogelijk te kunnen maken, gebruiken we het mede verschijnen van bedrijven in samenwerkingsverbanden op het gebied van O & O om de inter-industriële technologische complementariteit van 129 sectoren in Duitsland over een periode van meer dan 20 jaar te bepalen. De resultaten worden toegelicht in een zogeheten complementariteitsruimte voor de Duitse economie. De ruimte biedt inzicht in het potentieel van sectorparing voor complementair partneren in het delen van hulpbronnen. De bevindingen bevestigen voorts dat de sectoren intensief zijn verbonden binnen de gemeenschappen van andere sectoren maar nogal zwak zijn verbonden met sectoren die van andere gemeenschappen zijn. Daarnaast wordt het concept van complementariteit als inherent dynamisch beschouwd. Een voorbeeld daarvan is de gestage groei van de telecommunicatiesector en de ICT-gerelateerde sectoren.

Gezamenlijke subsidies voor O&O, technologische overeenkomsten en regionale innovatie

In hoofdstuk 5 maken wij een toevoeging aan de literatuur over de evaluatie van subsidies voor O&O door te beargumenteren dat de effecten van subsidies verder reiken dan een uitbreiding van monetaire middelen van de organisaties. Het hoofdstuk brengt de aanwezigheid van ten minste twee effecten naar voren die de grenzen overschrijden van een enkele organisatie. Het eerste effect betreft een samenwerkingseffect. Het tweede effect doet zich voor als consequentie van gesubsidieerde samenwerkingsprojecten en vertegenwoordigt een netwerkeffect. Het empirische onderzoek op het niveau van de Duitse arbeidsmarktregio's onderbouwt deze stelling. De resultaten tonen aan dat subsidies voor O&O-samenwerkingsverbanden weldegelijk van invloed zijn op regionale O&O-activiteiten. Ten tweede, de effectiviteit van O&O-subsidies voor O&O-samenwerkingsprojecten hangt sterk af van de juiste combinatie van samenwerkende bedrijven. Daarmee heeft het toegang verstrekken tot gerelateerde variëteit een positief effect op de innovatieve groei van een regio. Bovendien tonen wij in dit hoofdstuk aan dat centraliteit met betrekking tot gesubsidieerde interregionale O&O-samenwerkingsnetwerken waardevolle kennisoverloop mogelijk maakt. Dit wijst op sterke indirecte effecten in verband met het subsidiëren van gezamenlijke O&O-projecten die zelden worden overwogen in de bestaande literatuur.

Een gerelateerdheidsstandpunt met betrekking op de opkomst en ondergang van beroepsmatige specialisaties in Duitsland

Hoofdstuk 6 verkent of regio's een effectief orgaan zijn voor het coördineren van de expertise van verschillende medewerkers met het oog op de verscheidenheid van hun beroepen. Dit wordt gedaan door het aannemen van een gerelateerdheidsstandpunt op basis van patronen in regionale beroepsmatige co-specialisaties. De beroepsmatige compositie van een regio wordt verondersteld van belang te zijn voor dynamische regionale accumulatie van vaardigheden via het effect ervan op het arriveren (vertrekken) van gerelateerde (niet-gerelateerde) beroepsmatige specialisaties. Met gebruik van lineaire waarschijnlijkheidsmodellen blijkt in het hoofdstuk dat de waarschijnlijkheid van het arriveren van nieuwe beroepsmatige specialisaties in een regio met zes procent toeneemt als het niveau van gerelateerdheid rondom dit beroep met tien procent toeneemt. Dit effect is nog duidelijker als beroepen met intensief menselijk kapitaal in beschouwing worden genomen. Het tegenovergestelde effect van beroepsmatige relaties geldt voor de relatie tussen gerelateerdheid en vertrekaantallen. Een toename in gerelateerdheid van tien procent in dit geval draagt bij aan een afname in de waarschijnlijkheid van vertrek van beroepsmatige specialisaties van drie procent.

Conclusies

Hoofdstuk 7 vat de belangrijkste bevindingen van de dissertatie samen en geeft suggesties voor verder onderzoek. Over het algemeen bevestigen de bevindingen in de dissertatie de relevantie van gerelateerde variëteit in context. Daarmee geven de resultaten aan dat gerelateerdheid van nature multidimensionaal is en dat gerelateerdheidspatronen de dynamiek van regio's en technologieën vormgeven, ongeacht van welke dimensie-onderzoeken en maatstaven gebruik is gemaakt. Als gevolg daarvan kunnen de voorgestelde ruimten voor beroepen of overeenkomstigheid/complementariteit waardevolle inzichten opleveren voor het onderzoek naar (regionale) economische ontwikkeling en bijdragen aan het verstrekken van inzicht in de wijze waarop gerelateerde regionale economische evolutie werkt.

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Curriculum Vitae

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