Cluster Theory: Related Diversity and Employment Growth in Dutch Topsector ‘Life Science and Health’ Clusters

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ABSTRACT In this study regarding regional clustering, we have investigated the economic relevance of the Topsector 'Life Science and Health' in the current Dutch targeted sectoral state funding policies, i.e. 'Topsectoren Beleid.' By expanding said sectoral definition to include cognitively proximate related industries, we consider the theorised importance of (related) knowledge-spillovers in 'Life Science and Health' clusters. As such, we move beyond the traditional dyad in the long-standing debate in economic geography concerned with the importance of either regional specialisation or diversification to economic growth.

Identifying related industries is in no way without difficulties. It is only when we strictly abide by the classification method proposed by Boschma and Iammarino (2009), that we find compelling evidence for the direct beneficial effects of related industries collocating at 'Life Science and Health' clusters in this research.

With the exception of spinoffs dynamics, we also found indirect evidence of the importance of labour mobility and collaborative networking, i.e. mechanisms of the regional dissemination of related knowledge.

We suggest that quantitative analysis along this line of reasoning could perhaps be supplemented with detailed studies of the regional economic landscape to identify important related industries more concisely. This is particularly important when the 'Topsectoren Beleid' may prove to be in need of revising towards being inclusive of related diversity, provided that empirics will eventually surmount to a convincing body of proof for the economic relevance of related industries.

Key words: Cluster-based Theory • Specialisation • Related Diversity • Labour Mobility • Collaborative Networking

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1 Introduction

1.1 Research Topic

In the context of modern globalisation, increased competition results in global trends towards urbanisation, concentrating production at favourable locations, so making specific industrial clusters more important (McCann, 2008; McCann and Acs, 2010).

Policy makers now attempt to safeguard such specific places with targeted legislative actions to ensure the continued economic viability for the future.

Dutch national economic development policies, for example, steered away from even development policies in favour of targeted sectoral funding, called 'Topsectoren Beleid' as of 2011 (Ministerie van Economische Zaken, 2011; Raspe et al., 2012).

Regards this current economic development policies approach, the Dutch state government has identified several propulsive industries, including the *Topsector* 'Life Science and Health' under scrutiny in this research, as being of particular economic interest to the Dutch economy. Targeted funding is provided to ensure the economic competitiveness of these high-growth industries for the future (Raspe et al., 2012).

The rationale for this new line of legislative thinking has been explicitly informed by theoretical insights regarding the beneficial effects of industrial clustering, i.e. localised growth in the spatial economy (Gordon and McCann, 2000). Therefore, cluster-based theory will play a central role in researching the beneficial effects for one particular Topsector, namely 'Life Science and Health.'

Employing cluster-based theoretical insights in economic development policies appears to be a sensible strategy, as most industrial activity is shown to accumulate at certain locations heterogeneously, improving the success rate of firms located there (Krugman, 1991; McCann, 2001).

Firms agglomerate because proximity is necessary to benefit from geographically bounded localised externalities, limited by increasing spatial distance transactions costs, such as transportation costs, which diminishes net profits (Krugman, 1993).

But even though there is a limit to the positive externalities to locating at a cluster, e.g. increased local land prices, productivity gains more than compensate for that, underscored by the widespread occurrence of clustered regions (McCann, 2001).

Thus, locating at a cluster provides firms with a distinct competitive advantage *vis-à-vis* rather diversified locations. Essentially, clusters will stimulate local economic growth, as a result of productivity gains, improved innovative behaviour, and new business formation (Porter, 2000).

As such, this research will attempt to find evidence of the distinct advantages of clusters, and by doing so, attempt to provide improved empirical justification for the current targeted state funding policies program, i.e. 'Topsectoren beleid.'

Focusing solely on the Topsector 'Life Science and Health' in this research, appears to be a reasonable approach as this particular sector is highly innovative, knowledge-driven, and highly clustered (Centraal Bureau voor de Statistiek, 2012).

But the precise ways in which industrial clustering will benefit economic growth has sparked a long-standing debate in economic geography, which up until recently has focused on the dichotomy between *specialisation* and *diversification* of the dominant sectoral structure of a local economic system.

While specialisation results in intra-sectoral externalities, e.g. having a relevant local labour pool, proponents of diversification contend that urban, unrelated, inter-sectoral spillovers are key for achieving economic growth (Glaeser et al., 1992).

Even though the ongoing debate regarding the importance of either specialisation or diversification on economic growth has long been scrutinised, there remains a dearth in clear-cut evidence to make a case for the importance of either (Farhauer and Kröll, 2011).

Recently however, the debate has been extended to include a third context for achieving localised benefits, which is based on the evolutionary approach in economic geography, namely: *related diversity*. Besides firms being able to benefit from spatial proximity, some commonality in skills and routines will allow firms to successfully exploit the local inter-sectoral knowledge to their advantage (Boschma, 2009).

For example, Centraal Bureau voor de Statistiek (2012), i.e. the Dutch statistics office, suggests that there are close linkages between Dutch 'Life Science and Health' firms and other Topsectors, namely: 'Agro and Food' and 'High-tech Systems and Materials.' These inter-sectoral linkages can be considered part of the notion of related diversity, because even though the Topsectors are indeed in different sectors by definition, firms will share some degree of *cognitive proximity*, allowing for relevant local inter-sectoral knowledge-spillovers to take place between these industries. But, other sectors may also share some degree of cognitive proximity with the Topsector 'Life Science and Health.' Identifying these sectors will be part of this research.

Examining the beneficial effects of current Dutch targeted funding policies on economic growth in this research indeed makes sense, and has in fact been done in a publication called the 'Topsectoren Monitor' (Centraal Bureau voor de Statistiek, 2012). However, up until just very recently, such monitoring had not considered the theorised positive externalities deriving from related industries (see for example Weterings, et al., 2013).

As such, this research will go beyond the traditional theory dichotomy in economic geography regards the dominant sectoral structure of a local economic system, the debate of which up until recently has not been including related diversity in empirical studies (Boschma and Iammarino, 2009).

1.2 Research Questions

The previous section points out the relevance of researching economic growth of the highly innovative Dutch Topsector 'Life Science and Health.' As such, the research question is as follows:

> To what extent did (related industries at) specialised economic clusters in Dutch Topsector 'Life Science and Health' sectors improved economic growth of said sectors in the Netherlands, during the period 2006 to 2011?

To structure the research, a total of five sub questions will be addressed. Firstly, the evolution of Dutch national economic development policies over the last couple of decades will be discussed, leading up to the current 'Topsectoren Beleid,' including *inter alia*, targeted funding programs supporting 'Life Science and Health' sectors.

Secondly, Dutch regions will be scrutinised for regional specialisation in 'Life Science and Health' sectors to attempt to find evidence of spatial clustering in this sector.

Thirdly, provided such specialised regions occur in the Netherlands, we will look for evidence of improved economic growth at clustered regions compared to lesser specialised regions over the past five years.

Fourthly, to particularise the theorised externalities of clusters for attaining localised economic growth, we will attempt to look for evidence of additional positive externalities resulting from related industries collocating at 'Life Science and Health' clusters. Also, the potential beneficial effect of close linkages with other selected Topsectors will be scrutinised.

Lastly, the relation between the intra-sectoral build-up of 'Life Sciences and Health' sectors and economic growth in these sectors will be further investigated.

1.3 Aims and Goals

The goal for this research is to put cluster-based theory into practice in order to gain better insights into the theorised beneficial effects of clustering, and in particular to better understand the role played by related industries. The theorised economic importance of the latter has been suggested by several authors in connection to the field of evolutionary economic geography (Boschma, 2009).

Because of the novelty of operationalising related diversity research, there is still a dearth in empirical results which can still be expanded on, in order to gain improved insights into the relevance of related diversity for the economic growth of clusters.

Lastly, the current Dutch targeted economic development system in connection to the 'Topsectoren Beleid' may eventually prove to be in need of revising towards being inclusive of related industries, provided that empirics will ultimately surmount to a convincing body of proof of the economic relevance of related industries.

1.4 Outline

The remainder of this research is structured as follows. Section 2 will discuss the political background of the current Dutch 'Topsectoren Beleid,' and the Topsector 'Life Science and Health' in particular. Section 3 will provide a literature review on the topic of clustering and related diversity. Section 4 will discuss the methodology for this research, followed by the results in section 5. Section 6 will discuss the implications of the results. Finally, section 7 will provide any conclusions that can be distilled from this research.

2 Background Topsectoren Policies

2.1 Pieken in de Delta

After a period of inclusive economic development policies called 'egaliseringsbeleid,' as of 2006 'Pieken in de Delta' as the spatial component of the 'Nota Ruimte' policies plan formed a stark break with preceding legislation by focusing specifically on targeted regional development (Raspe et al., 2012).

This change was in tandem with a broader *fourth wave* trend in state legislation towards cluster-based targeted policies (Glasmeier, 2000). This renewed focus on the importance of clusters had been sparked by three key publications around that time, namely Scott (1988), Piore and Sabel (1984), and Porter (1990). This surmounted to a general consensus of the need for safeguarding economic clusters for economic growth (Krugman, 1991; McCann, 2001).

Although continuous efforts were made for improving the overall business climate in the Netherlands, the Dutch government steered away from traditional 'blueprint' planning in favour of a decentralised approach aimed at improving six core areas of particular economic interest, i.e. concentrations of economic activity, for ensuring the continued competitiveness of the overall Dutch economy. For each of the six core regions, specific 'perspectives' were devised to maintain the economic propulsive power of each of those regions (Ministerie van Economische Zaken, 2004).

2.2 Topsectoren Policies

In order to maintain the strong international economic position of the Netherlands, the Dutch government moved away from subsidiary-based stimulation programs in favour of the current targeted sectoral economic development policies system, i.e. 'Topsectoren beleid' (Ministerie van Economische Zaken, 2011).

Instigated by the Dutch House of Parliament in 2011, several multi-disciplinary teams comprising members with a background in business, research, or legislation, devised sets of recommendations for improving the competitiveness in several sectors of the Dutch business environment. An additional team was devised to specifically investigate the cross-cutting field of branch offices. The teams' recommendations focused on stimulating Dutch businesses to invest, innovate, and export.

Following from these sets of recommendations, in 2011 the Dutch government appointed nine sets of sectors of particular interest in its economic development policy, called 'Topsectoren.' Sectors were identified based on the following four criteria: knowledge-intensive; export-oriented; having targeted legislations; and, potentially benefitting public interest.

The selected nine Topsectors comprise: 'Agro and Food;' 'Chemicals;' 'Creative Industry;' 'Energy;' 'High-Tech Systems and Materials;' 'Horticulture;' 'Life Science and Health;' 'Logistics;' and, 'Water' (Ministerie van Economische Zaken, 2011).

The ambition of the Dutch government is for the Netherlands to be ranked in the top five of most knowledge-intensive economies in the world by 2020, to increase total R&D expenditure to 2,5 per cent of GDP by 2020, and to have increased private sector expenditure through public private partnerships up to 40 per cent by 2015 (Ministerie van Economische Zaken, 2011).

2.2.1 Topsectoren Monitoring

Resulting from the preliminary results carried out by the Dutch statistics agency, close to a quarter of all Dutch firms pertain to the 'Topsectoren' (measured in 2010; some 264,220 firms), accounting for around 38 per cent of the entire gross Dutch national production, of which some 40 per cent is destined for export, excluding the creative industry sector. Most strikingly though, over 96 per cent of firms pertaining to 'Topsectoren' indicate to internally fund research and development activities.

As regards employment, the Topsectors account for an approximate 21 per cent of national full-time equivalent jobs (Centraal Bureau voor de Statistiek, 2012).

According to the Dutch national statistics agency, innovation in firms can be considered either technological innovation or non-technological innovation, e.g. marketing or organisational changes, or both (Centraal Bureau voor de Statistiek, 2012). This definition indicates half of all Dutch firms having 10 employees or more to be considered innovative, not differentiating between Topsectors or otherwise.

However, innovation expenditure differs between the entire Dutch business population, and the Topsectors in particular, about €8,5 billion of the total investments of over €13 billion is accounted for by the Topsectors alone in 2010 (Centraal Bureau voor de Statistiek, 2012).

2.2.2 Life Science and Health

Dutch firms pertaining to the Topsector 'Life Science and Health' are considered to be highly clustered, innovative, and technology-intensive, and are generally involved with the health of either people or life stock. The sector is considered one of several growing sectors in the Dutch economy (Ministerie van Economische Zaken, 2011).

The Topsector comprises three broad fields, namely (1) pharmaceuticals; (2) medical instruments; and, (3) health-related research (Centraal Bureau voor de Statistiek, 2012). Appendix A provides an overview of all sectors of the Topsector 'Life Science and Health.'

Firms in this sector share close linkages with other Topsectors, including 'Agro and Food' and 'High-tech Systems and Materials.' For instance, the province of Noord-Brabant is making investments to advance these linkages, aiming to broaden the connection of the *Life Science park* of Oss with the *Food and Health park* 'Fhealinc' in Den Bosch and the medical innovations cluster in Eindhoven (Ministerie van Economische Zaken, 2011). (The importance of having strong linkages will be discussed in chapter 3.)

Also, the Dutch home market is considered to be a seedbed for health-related innovations, some 57 per cent of these innovations will subsequently find its way to the international market (Centraal Bureau voor de Statistiek, 2012; Topteam Lifesciences and Health, 2012).

According to the 'Topsectoren' Monitor carried out by the Dutch statistics agency and following from table 2.1 below, Topsector 'Life Science and Health' is small compared to the other Topsectors, yet its 2,290 firms accounted for around 39 thousand jobs, and some 13 per cent of total R&D expenditure in the Netherlands in 2010.

Innovation expenditure measured as a percentage of total sectoral added value in this sector strongly exceeds expenditure of that in other Topsectors, and in fact exceeds expenditure in the entire Dutch business population as well (details in table 2.1 below; Centraal Bureau voor de Statistiek, 2012).

A striking characteristic of 'Life Science and Health' firms is the relatively high share of large firms (over 250 employees) compared to all other Dutch industrial sectors: 1%, and 0.3%, respectively, as well as a higher average firm size, namely 19 employees per firm, compared to 8 employees per firm for the rest of the Dutch firm population (Centraal Bureau voor de Statistiek, 2012).

Table 2.1 Key Indicators of the Lifescience and Health sectors 2010

	Tot. no. firms	Production	Tot. Added Value	Export of production	R&D expen-ditures	Tot. no. employees (in fte)
	Abs.	Mil. Euro	Mil. Euro	Mil. Euro	Mil. Euro	x 1000
Total Sector	2.290	12,616	2,640	7,156	671	39
Pharma-ceuticals	180	6,230	1328	4577	382	14
Medical Equip.	1,650	5,777	1,157	2,514	137	19
R&D	460	609	156	66	151	6

(Source: Centraal Bureau voor de Statistiek, 2012)

3 Theoretical Background

3.1 Clusters and Economic Growth

As most industrial activity has been shown to accumulate heterogeneously at specific locations as a result of regional specialisation (Krugman, 1991; McCann, 2001), the concept of industrial clustering, i.e. localised growth in the spatial economy, has gained a lot of scholarly attention amongst a variety of disciplines (Gordon and McCann, 2000).

Locating at a cluster provides firms with a distinct competitive advantage compared to other locations (Porter, 2000), as clusters allow for localised increasing returns to scale, improving the success rates of firms located there (Krugman, 1991).

Firms agglomerate at cluster locations, because proximity needed for returns to scale is geographically bounded, limited by increasing spatial distance transactions costs, such as transportation and communications costs, all of which diminish net profits (Krugman, 1993).

Even though there is a limit to the positive externalities of locating at a cluster, e.g. increased costs of factor inputs, productivity gains more than compensate for that, underscored by the widespread occurrence of clusters (McCann, 2001).

However, the precise meaning of industrial clustering is ambiguous (Gordon and McCann, 2000). According to Porter (2000), a cluster is "a geographical proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities (p. 254)," the spatial scope of which can range from a city up to and across national borders.

Depending on the extent to which a cluster is specialised, "(…) most include end-product or service companies; suppliers of specialised inputs; components; machinery, and services; financial institutions; and firms in related industries (Ibid., p.254)."

Furthermore, clusters will have downstream industries; educational institutions; and technical support. Lastly, influential regulatory agent departments may be regarded part of a cluster as well (Ibid.).

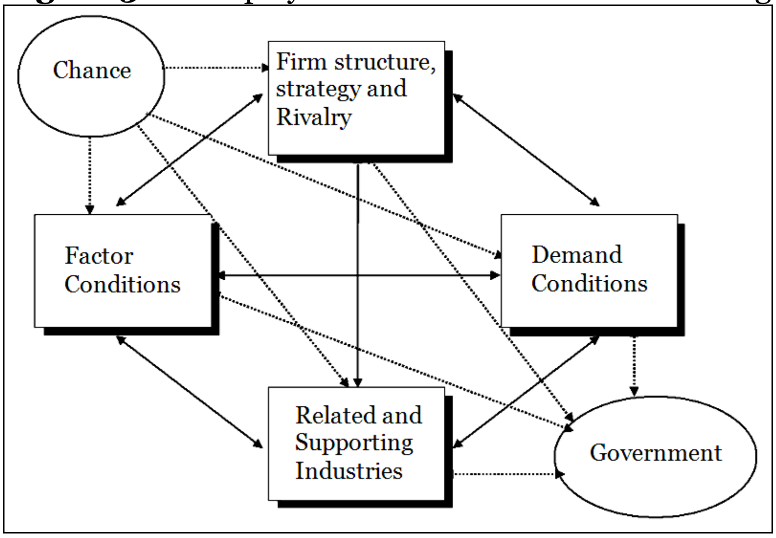
Taking all these influences into account is important because, apart from urbanisation economies and Jacobs' externalities (see section 3.2.2 below), cluster-specific aspects of the business environment exert the strongest influence on attaining competitive advantages at such locations (Porter, 2000).

To structure research on the cluster-specific determinants of competitiveness at any location, Porter, in his seminal book *The Competitive Advantage of Nations* (1990), devised a theoretical model depicting four interrelated factors, as well as two exogenous influences, generally known as the *Porter Diamond* (see Figure 3.1).

The end result of the interplay of these locational influences is a local milieu that stimulates (collective) investment in multiple ways for continuous upgrading the competitive environment.

Porter (2000) proposes three distinct ways in which a cluster will shape and indeed improve the local competitive advantage. These include (1) increasing the productivity of firms; (2) facilitating innovative behaviour; and (3) stimulating innovative start-ups and spin-offs. These three mechanisms will now be discussed in more detail.

Figure 3.1 Interplay of locational influences and exogenous influences



(Source: Porter, 1990, p. 127)

3.1.1 Productivity of Firms

Firstly, clusters stimulate the productivity of firms in several ways. Access to competitive local inputs and labour results in efficiency gains, e.g. local outsourcing, will lower spatial transaction costs compared to sourcing from more distant locations.

Notably, improved demand will, in turn, increase the supply of (the quality of) inputs and labour which, under the influence of heavy competition of similar firms, will be a distinct localised advantage.

Information and (tacit) knowledge will accumulate at cluster locations which can therefore be accessible by firms in proximity at a lower price, potentially improving productivity. Firms can rely on other local firms in production, marketing, *et cetera*, cf. *complementarities*, as all members rely on each other at any given location. In addition, availability of local institutions and quasi-public amenities will be more likely, because shared usage lowers relative costs. In fact, knowledge can be viewed as a quasi-public good as well (Porter, 2000).

3.1.2 Innovation

As the concept of innovation is used differently in a wide variety of contexts, defining it can be rather problematic. Generally, innovation can be either product or service innovation or process innovation, which are considered highly interlinked processes in a firm's development activities (Gordon and McCann, 2005).

Innovative behaviour is commonly associated with the way in which clusters allow for localised learning processes (Glaeser, 1999). Marshall (1920) argues that the free flow of vital (tacit) knowledge is bounded geographically to a cluster location. These (inter-industry) learning processes heavily depend on the mobility of workers through local (informal) connections between firms, as well as new spin-off firms. Labour mobility will therefore increase the local (tacit) knowledge build-up which will buttress the development of new innovations (Keeble and Wilkinson, 1999).

Thus, spatial proximity enables establishing close-knit relationships which allow, *inter alia*, for perceiving (buyer) firms' needs more quickly. This is aided by the availability of opportunities and flexibility provided by the access to new innovative technologies, skills, components, and transport systems (Porter, 2000).

As such, clustering facilitates the creation of new innovative products and processes (Saxenian, 1994). Intense local competition with many rivals operating in the same context of costs, labour, *et cetera*, intensifies the pressure for innovative behaviour leading to a continuously improving competitive advantage that is hard to duplicate elsewhere (Porter, 1990; 2000). A plethora of studies — including Jaffe et al. (1993), Glaeser (1999), Malecki (1979a), Rauch (1993), and Saxenian (1994) — corroborate this view.

As regards economic development policies, three key publications (see overview in section 2.1) sparked a renewed interest in attempts to encourage innovative behaviour through *fourth wave* regional development policies (Glasmeier, 2000; Sternberg, 1996).

Similarly, policy makers contend that some recurring characteristics of successful innovative regions can be replicated elsewhere through planning intervention, such as (in)formal knowledge sharing between small firms through flexible, reciprocal linkages (Keeble et al., 1999; Rogerson, 1993; Scott, 1988). Yet, there remains a dearth in the empirical proof of the validity of this notion (Gordon and McCann, 2005).

3.1.3 New Business Formation

Lastly, clusters support a new business formation which arguably improves the local competitive advantage for proximate firms to benefit from (Porter, 2000). For instance, the occurrence of a cluster in itself is an indicator of — and information about — opportunities to exploit. This potentially stimulates employees to terminate their current contract in order to start new businesses themselves. Furthermore, as spinoff-entrepreneurs are likely to locate in proximity of their former employer, knowledge formation tends to be spatially bounded to the cluster (Klepper, 2007).

In addition, entry barriers for locating at a cluster are lower than elsewhere, as many of a firm's necessary inputs are readily available at such locations. Similarly, barriers to exit are lower as well, e.g. due to the reduced need for specialised local investments.

Employing Schumpeter's (1942) '*Creative Destruction*' argument, intense competition combined with entry and exit dynamics will lead to a continuously improving average quality of business environment (Porter, 2000; Schumpeter, 1942).

In short, Schumpeter's (1942) 'Creative Destruction' argument explains how new potentially fitter market entrants challenge incumbent firms to improve their performance, otherwise making them liable for firm disbanding. Only suitable new entrants and indeed the remaining high-quality incumbents will remain active.

3.2 Localised Competitive Advantage

As outlined in the preceding section, locating at a cluster provides firms with a distinct competitive advantage compared to other locations (Porter, 2000). This is so because clusters allow for localised increasing returns to scale, improving the success rates of firms located there (Krugman, 1991).

However, the precise way in which industrial clustering will benefit economic growth, has sparked a long-standing debate in economic geography. Glaeser and colleagues (1992) put forward the contention that important localised knowledge spillovers and learning effects result from intense interaction in the *same* or *different* sectors at urban areas, because "[p]hysical proximity facilitates this free information transmission" (Ibid., p. 1131).

There is now a large body of literature regarding the debate on whether regional specialisation or diversification is the key driver for the dissemination of local knowledge, and, thus, regional growth (see, e.g. Boschma and Iammarino, 2009). Put differently, do firms learn from local similar firms, or will knowledge spill over between industries?

While specialisation stresses the importance of intra-sectoral externalities, e.g. having a relevant local labour pool, supporters of a diversified sectoral structure argue that inter-sectoral spillovers embedded in any urbanised region are important for economic growth.

Even though the debate on the importance of either specialisation or diversification to economic growth has long been scrutinised, clear-cut evidence to make a case for the importance of either is lacking, partly because of the wide variety of indices employed to capture the degree of either sectoral structure (Farhauer and Kröll, 2011). Specialised regions tend to yield productivity gains. For example, Capello (2002) showed the primacy of localisation gains over urbanisation economies for the high-tech sector. In addition, regional diversification has been linked to improved employment growth (Frenken et al., 2007; Glaeser et al., 1992).

Recently, however, the debate has expanded to include a third explanation for localised benefits, namely, related diversity. Based on the evolutionary approach in economic geography, advocates of the importance of having local related industries suggest that, besides geographical proximity, there should also be some commonality in firms' skills and routines, cf. cognitive proximity, for firms to successfully exploit the local (tacit) inter-firm knowledge to their advantage, benefitting regional economic growth (Boschma, 2009; Farhauer and Kröll, 2011).

As noted in Chapter 1, this research will attempt to contribute to the empirical evidence of having local related diversified industries by investigating the connection between the Dutch Topsector 'Life Science and Health' and its related industries.

To recap the previous section, Porter (2000) suggests three ways in which a cluster will shape local competitive advantage which can now be linked to the main sectoral structure of any regional economy.

Firstly, productivity gains and new firm start-ups will most likely be linked to the arguments of specialisation, whereas diversification is considered fundamental to innovative behaviour. Lastly, related diversity can be considered important for the stimulation of innovative behaviour and increased productivity. Cluster theory in connection to specialisation, diversification, or related diversity will now be discussed.

3.2.1 Specialisation

Specialised regions allow for local, sector-specific, specialised (factor) inputs, such as natural and human resources, knowledge, capital, and infrastructure (Porter, 1990). These intra-sectoral externalities will enable cluster members to achieve productivity gains, as well as attract new, similar firms and start-ups (Porter, 2000).

As regards firms pertaining to the same industrial sector, in Marshall's (1920) classical schema, sources of agglomeration economies are understood as being external to individual firms, yet result in economic growth for every firm located in proximity. The sources for these scale economies can be understood by the presence of (1) information spillovers; (2) local non-traded inputs; and (3) a local skilled labour pool.

According to Marshall (1920), the first source for benefitting from agglomeration externalities at clusters involves tacit knowledge spillovers. As many firms pertaining to an industry are in each other's proximity, their employees are also close, allowing for informal, partial, non-codified information sharing, e.g. related to new technologies or market trends. Proximity, therefore, constitutes an important condition for optimal knowledge-sharing, providing clustered firms with an information advantage over the firms located outside of an industry-specific cluster (Romer, 1986).

Efficient and innovative knowledge employment enables firms to create economic value (Mahoney, 1995). However, de Bok and van Oort (2011) suggest that "[f]irm-specific characteristics may [...] precondition whether a given firm can profit from externalities" (Ibid., p. 7).

Secondly, Marshall (1920) argues that clustering allows for efficiency gains by sharing costly local specialist inputs amongst firms from the same industry. Baring these costs among several firms allow for such service provisions at a lower cost. These local inputs are considered non-traded, as they are not a part of those firms' production inputs as such. The costs will fall further with more comparable firms co-locating in proximity.

Lastly, Marshall (1920) suggests that clustering of firms in the same industrial sector gives rise to a specialised local labour pool, reducing firms' labour acquisition costs and also reducing the (extremely high for some industries) costs of training specialised personnel.

In sum, agglomeration economies allow firms pertaining to a specialised cluster to achieve productivity gains compared to locations elsewhere.

Alternatively, Hoover's (1937; 1948) classification of agglomeration economies is not restricted to a single industrial sector *per se*, and comprises (1) firm-specific internal returns to scale; (2) industry-specific localisation economies; and (3) city-specific urbanisation economies.

Internal returns to scale are agglomeration economies that arise solely in the production by large firms resulting from their sheer size and are regarded as internal to a firm (Hoover, 1937; 1948). Yet, the resulting agglomeration economies are explicitly spatial, as high concentrations of investment and people take place in a single location (McCann, 2001).

Secondly, sector-specific localisation economies accrue to all firms located in a cluster. As argued by Marshall (1920), agglomeration economies arising from information spillovers, local non-traded inputs, and a local skilled labour pool apply.

Lastly, city-specific urbanisation economies benefit every firm in a cluster. Urban areas are considered places with easy access to information and knowledge that allow for internal and external R&D to take place effectively, which can lead to more process and product innovations (Davelaar and Nijkamp, 1989). Moreover, urban density increases the probability of educational institutions to locate there as well. Intensive interaction in cities provide access to information and knowledge essential for creativity and innovativeness (Andersson, 1985; Malecki, 1979b). This point will be further discussed in the next section.

3.2.2 Diversification

As regards the debate concerning the optimal local sector structure of an economy, diversity may be important for increasing a region's competitiveness. Diversity is considered to be foundational for innovative behaviour to take place at clusters. Alongside with sophisticated home market *demand conditions,* the need for innovative behaviour to cope with such advanced demands grows as well, which, in turn, increases competitiveness of firms (Porter, 1990). In addition, intense local competition stemming from the 'visibility' of direct competitors stimulates innovative behaviour (Jacobs, 1960; Porter, 1990) and is considered to be important for economic growth (Krugman, 1991).

Jacobs (1960) conjures that industry diversity is particularly important for high-quality knowledge spillovers. A resulting deep division of labour will stimulate inter-industry innovative behaviour, in agreement with Schumpeter's (1942) argument that entrepreneurs recombine old ideas into new, competitive innovations. Much previous research supports the notion of successful inter-sectoral knowledge spillovers. For example, Bairoch (1988) concurs by suggesting that being located at a diversified cluster encourages problem-solving agents to look for solutions outside their own industry.

Chinitz (1961) suggests that the firm size distribution, as well as the range of different types of industries located in a cluster, may be foundational for the growth of a cluster. Large firms located in a cluster may internally provide most of their required services resulting from scale economies. This will most likely render such services unavailable for new cluster entrants that, in their start-up phase, may heavily depend on locally available services, and, thus, supply interdependencies can in this case be considered as being external diseconomies (Chinitz, 1961).

Alternatively, supply interdependencies can be considered external economies when new entrants are in the presence of *incubator* firms. Such firms offer numerous types of services and resources (Löfsten and Lindelöf, 2001). A wide range of intermediate goods and services relationships with *incubator* firms allow for localised agglomeration economies. The presence of these firms will thus facilitate the successful development of new start-ups advancing economic development as such (Acs, 2006; Acs et al., 2008).

Furthermore, larger-scale clusters will support a broader range of types of industries, making them less susceptible to economic shocks *vis-à-vis* smaller, less diversified regions. Accordingly, as potential losses of a few industries will have less impact on the aggregate growth rate (Chinitz, 1961), more diversified clusters will result in more stable growth rates over time.
In sum, the model suggests that the firm size distribution and the range of different types of industries located in a cluster may be foundational for the growth of the cluster (Chinitz, 1961).

Now, the arguments of Chinitz (1961) can be extended to consider the effects of firms locating at a science park, cf. *academic incubator milieu*, as 'Life Science and Health' firms collocating with academic research and development firms that are explicitly taken into account in this research.

An *academic incubator milieu* is of great importance to entrepreneurs in at least two distinct ways and allows for establishing diverse, collaborative networks, as well as for promoting linkages (Schwartz and Hornych, 2010).

As mentioned above, new firms lack the crucial connections that have yet to be established in order for these firms to become successful in the long run. Efficient networking enables these firms to establish qualitative, (in) formal partnerships between academic institutions and other firms at an early stage (Hansen et al., 2000; Lindelöf and Löfsten, 2004; Uzzy, 1997).

Moreover, linkages with *academic incubators* allow for knowledge transfers improving innovative behaviour in smaller firms and are, therefore, expected to improve the success rates of these firms (Schwartz and Hornych, 2010).

Contrary to private sector start-ups, academic spin-offs located at science parks will most likely be involved in research and development (Oakey, 1995), and, *inter alia*, are expected to have a higher propensity to engage with external information sources, including academic institutes, consultants, and entrepreneurs (Lorenzoni and Ornati, 1988).

However, Schwartz and Hornych (2010) found that industry effects are more important to the success of young firms located at specialised incubator milieus. In their analysis of science parks in the Benelux, van Dierdonck and colleagues (1991) found that, although most ventures do have ties with an local academic incubator, only a small portion of those linkages become formalised into R&D partnerships.

3.2.3 Related Diversity

As mentioned above, the evolutionary approach in the field of economic geography is explicitly considered in this research when investigating the way in which related diversity impacts regional growth, i.e. through a particular mechanism for localised knowledge-spillovers. As such, the notion is closely linked to the *related and supporting industries*, which produce cost-effective inputs in support of local innovation and increased firm productivity (see Porter, 1990).

Contrary to e.g. Jacobs' ideas outlined in the preceding section, a diversified regional economic landscape may not necessarily result in knowledge spillovers between *unrelated* industries. In fact, there should be some common ground in production activities to be able to employ the available inter-industry knowledge to a firm's advantage, as such knowledge should 'make sense' (Boschma and Iammarino, 2009).

Thus, for local knowledge to be effectively employed in any subsequent industry, some *cognitive proximity* is required as well (Nooteboom, 2000). However, there is a *proximity paradox* in that there is a limit to the degree of cognitive proximity (Boekel and Boschma, 2012). Moreover, any region that is specialised in related diversity will be more likely to efficiently support localised learning and innovative behaviour because those "(…) sectors that are related in terms of shared or complementary competences" (p. 292-293; see also Boschma, 2005; Frenken et al., 2007; Boschma and Iammarino, 2009).

Related diversity thus builds on the local (tacit) knowledge, resulting from path dependency (Boschma and Wenting, 2007; Klepper, 2007; Martin and Sunley, 2006). Exploiting such unique regional endowments is considered to be foundational to regional growth (Boschma, 2009; Porter, 1990). Several studies corroborate this view (e.g. Boschma and Iammarino, 2009; Frenken et al., 2007; Neffke and Henning, 2008).

Along similar lines as Porter's views regarding the mechanisms for improving the competitiveness of a cluster, Boschma (2009) suggests three localised mechanisms that allow for the regional dissemination of *related* knowledge while building on local assets, namely (1) spinoffs (routines); (2) labour mobility (skills); and (3) efficient networking.

First, firm-specific organisational routines are a determinant of a firm's productivity. Successful routines will not only remain, cf. *survive*, in the region but will be disseminated to other local firms, branching out regionally into related routines (Frenken and Boschma, 2007), albeit only to firms in *cognitive proximity*. This effectively works like a selection mechanism for the knowledge creation in any specialised region (Boschma, 2009; Gertler, 2003).

The dispersion of those routines can be considered an evolutionary selection process, as the routines may get altered ever so slightly with every transmission (Boschma and Frenken, 2011; Teece et al., 1997). However, the transfer of knowledge and routines is restricted to the local business environment because of its main drivers, i.e. spinoffs, and labour mobility, which are both local processes by nature (Klepper, 2007; 2010).

Moreover, the importance of labour mobility (and new firm formation) for disseminating or indeed retaining, local, unique (tacit) knowledge has been suggested above in connection to innovation (see section 3.1.2 and 3.1.3). The notion of related diversity adds to these arguments that again cognitive proximity, i.e. skills *related* to a worker's previous capacity, result in strong inter-industry labour flows between skill-related industries (Neffke and Henning, 2010). This is because skills from one industry can often be employed in other industries as well, i.e. skills are *fungible* between related industries. Furthermore, as most job moves will take place within a region, related inter-industry labour flows will add to the local knowledge pool (Boschma, 2009).

The last mechanism that allows for the regional dissemination of *related* knowledge is efficient networking. This has already been discussed in connection to the incubator model (see section 3.2.2). To recap, collocating with *academic incubators* provides innovative entrepreneurs, cf. spinoffs, with diverse collaborative networks at an early stage (Schwartz and Hornych, 2010).

This will compensate for the lack of crucial connections needed by new firms so that to become successful in the long run, as academic spinoffs are highly dependent on local external information sources (Lorenzoni and Ornati, 1988).

Boschma (2009) argues that networks transfer, say circulate, knowledge within a region because networks depend on social proximity. And certainly, the mechanisms for disseminating knowledge discussed above will have a strong influence on how knowledge transfers through a network locally, e.g. through social ties with former employers.

Boschma and Iammarino (2009) found that extra-regional trade linkages may also positively contribute to the local knowledge, provided that the knowledge is in an industry cognitively related to the local industries.

However, networks may also hinder productivity, e.g. when an inward focus results in extra-regional developments going unnoticed. Such ties should not be too rigid so that to avoid negative lock-in (Grabher, 1993).

To sum up, the recent notion of related diversity may particularise the debate regarding the importance of either regional specialisation or diversification for economic growth by also considering cognitive proximity in the regional dissemination of (tacit) knowledge, which is assumed to be the most important endowment of any innovative region for continued economic growth. Yet, empirical evidence thereof is scarce. Therefore, the present research will attempt to contribute to this area by considering the parallel effect between the Dutch 'Life Science and Health' sectors and the related diversified industries.

3.3 Hypotheses

For empirically testing several locational aspects of Dutch 'Life Science and Health clusters' (abbreviated as LSHC) in the Netherlands, several hypotheses will be tested.

As suggested in the introduction, LSHCs are shown to be highly specialised (Ministerie van Economische Zaken, 2011). Given the dominant structure of a location (Gordon and McCann, 2000), Porter (2000) posits that industrial clustering enables its members to gain positive externalities unattainable elsewhere through three spatially bounded mechanisms.

First, localisation economies stemming from (input) factor complementarities, i.e. (tacit) information spillovers, non-traded inputs sharing, and a relevant labour pool (Marshall, 1920) amplify the productivity of cluster members (Porter, 2000).

Clusters enable localised learning processes (Glaeser, 1999), which combined with the high visibility of competitors and home market *demand* opportunities stimulates the development of new innovations (Porter, 2000).

Lastly, Location-specific social networks (Granovetter, 1973; 1985) based on reciprocal trust allow for (in)formal high risk collaborations which also may compensate for the lack of essential connections, with *inter alia*, academic incubators, as 'Life Science and Health' firms are shown to be highly dependent on external information sources for their R&D activities (Chinitz, 1961; Hansen, et al., 2000; Lorenzoni and Ornati, 1988; Schwartz and Hornych, 2010).

Moreover, according to Scott (1988), clusters with a firm size distribution hinging strongly towards SMEs are a prerequisite of successful innovative behaviour, because these new industrial areas support the necessary close interaction of social, political, and economic relationships (Rogerson, 1993).

In fact, the close-knit interplay of buyers, supplier, and institutions are now considered foundational for understanding the competitiveness of a region (Porter, 2000). This signals new members to enter the region (Klepper, 2007), and forms an incentive for outside firms to migrate to the region as well due to lowered barriers to entry, which will advance the local competitive advantage further (Porter, 2000).

As such, regional specialisation in 'Life Science and Health' sectors is expected to result in improved (employment) growth in this sector in comparison with lesser specialised regions, accordingly, the first hypothesis is:

> H1. Employment growth in Dutch 'Life Science and Health' industries at LSHCs is higher compared to regions that are not specialised in said industries in the period 2006 to 2011.

Founded in the evolutionary approach in economic geography, the notion of related diversity adds to the arguments of Porter (1990) regarding the beneficial effects of *related and supporting* industries locating at LSHCs.

Basically, for local knowledge to be effectively applied in any subsequent industry as well, some cognitive proximity, i.e. relatedness, is required (Nooteboom, 2000).

Any region that is specialised in related diversity will therefore be more likely to efficiently support localised learning and innovative behaviour through local routines, skills, and, efficient networking (Boschma, 2009), because related industries share some degree of commonality in production (Boschma, 2005; Frenken et al., 2007).

Firms located at LSHCs are considered to be highly involved in R&D activities, which is by definition innovation-driven and therefore suitable to benefit from, or indeed support, industries in cognitive proximity. For instance, there is evidence of direct linkages between the Life Science and Health sectors and two other Topsectors, namely: 'Agro and Food' and 'High-tech Systems and Materials' (Ministerie van Economische Zaken, 2011), making a case for some degree of shared cognitive proximity between these sectors. As such, the hypotheses are:

> H2. Employment growth at Dutch LSHCs develops in parallel with employment growth in regional cognitively related industries (i.e. related diversity) in the period 2006 to 2011;

> H3. Employment growth at Dutch LSHCs develops in parallel with employment growth in the Topsectors 'Agro and Food' and 'High-tech Systems and Materials' in the period 2006 to 2011.

The last mechanism that allows for the regional dissemination of *related* knowledge is efficient networking.

This has already been discussed regards the incubator model in section 3.2.2. To recap, collocating with *academic incubators* provides innovative entrepreneurs, cf. spinoffs, with diverse collaborative networks at an early stage (Schwartz and Hornych, 2010). This will compensate for the lack of crucial connections new firms need in order to be successful in the long run, as academic spinoffs will be highly dependent on local external information sources (Lorenzoni and Ornati, 1988). As such, the last hypothesis is:

> H4. Employment growth at Dutch LSHCs depends on the presence of the subset of R&D related LSHC academia and medical centres as well as subsequent related diversified sectors in the period 2006 to 2011.

4 Methodology

4.1 Sample Data

This research comprises statistical analysis of the Dutch establishments population to attempt to find evidence of improved economic growth of 'Life Science and Health' sectors at cluster regions *vis-à-vis* more diversified locations in the Netherlands. Particularly, the importance of related diversity, i.e. industries in cognitive proximity, collocating at these clusters will be scrutinised.

The research will employ data from two separate sources, firstly, the Dutch LISA data set (www.lisa.nl) includes information about regional employment following the standard hierarchical industry classification system used in the Netherlands (i.e. 'Standaard Bedrijfsindeling 2008,' abbreviated as SBI 2008). Using employment data appears to be a sensible strategy because inter-industry labour flows between skill-related industries tend to be restricted to a region and will therefore add to the local knowledge pool, as is under scrutiny in this research (Neffke and Henning, 2010; Boschma, 2009).

Secondly, ancillary Statline data as provided by the Dutch national statistics agency will be used to control for several aspects in the business environment.

Analysis concerning the overall development of the Dutch Topsector 'Life Science and Health' will employ data between 1996 and 2011, whereas the estimating equations used for investigating the potential beneficial effects of both industrial clustering and related diversity will use data between 2006 to 2011. Narrowing the period of analysis for the latter part of the research is to avoid potential problems arising from sectoral classification changes made to the LISA data set as of 2006.

4.2 Measures

4.2.1 Dependent Variables

The regression models for this research will use employment data regarding Dutch 'Life Science and Health' sectors. Specifically, two types of estimating equations will be tested in this research, using as its dependent variable either employment growth between 2006 and 2011 (variable DELTA.JOB.LSH); or alternatively, the level of employment in 2011 (variable JOB.LSH.11).

4.2.2 Independent Variables

The estimating equations for this research will include several independent variables, two of which are of particular interest in this research, namely regional specialisation in 'Life Science and Health' sectors; and secondly, regional specialisation in related diversified industries. Provided there is indeed employment growth at specialised 'Life Science and Health' clusters, by doing so we attempt to disentangle the theorised positive effects of both clustering and related diversity on employment growth in 'Life Science and Health' sectors in this research.

Regional specialisation in industries pertaining to the Topsector 'Life Science and Health' (abbreviated as LSH) is measured by calculating a locational quotient (abbreviated as LQ) for every region in the Netherlands for 2006 and 2011, at the municipality level and the broader NUTS 3 level (variable LQ.JOB.LSH.6, LQ.JOB. NUT.LSH.6, LQ.JOB.LSH.11, LQ.JOB.NUT.LSH.11, respectively).

Using two geographical levels in this research is indeed to take into account any difficulties with accurately defining the spatial boundaries of any cluster as discussed in section 3.1. This will also to some degree account for any extra-regional linkages that may occur in the Netherlands.

The locational quotient LQ_{LSHr}, be it calculated at the municipality level or NUTS 3 level, is defined as the ratio of the regional proportion of employment E in LSH in any region r at the municipality level, relative to the national proportion of employment n in LSH, or:

$$LQ_{LSHr} = \frac{E_{LSHr}}{E_r} \Big/ \frac{E_{LSHn}}{E_n} .$$

For any region r, LQ_{LSHr} denotes the locational quotient regarding specialisation in LSH sectors, E_{LSHr} represents the level of employment in LSH sectors, E_r represents the total regional employment. E_{LSHn} is the national employment in LSH sectors, and E_n represents the total national employment.

As such, any region, be it at the municipality level or NUTS 3 level, having a LQ_{LSHr} higher than 1 has proportionally more employees in 'Life Science and Health' sectors compared to the Dutch national average, and is therefore considered to be regionally specialised in 'Life Science and Health.'

Notably, because every model will include the regional specialisation in 'Life Science and Health' variable LQ_{LSHr} at the municipality level and the NUTS 3 level simultaneously, the sum of jobs in 'Life Science and Health' sectors used to calculate the latter will not include the jobs in the same sectors of that municipality so not to account for those jobs twice.

Regional specialisation in related diversity is defined in a similar fashion as above, by calculating the yearly regional LQ for related diversified industries at the same two geographical levels. So, any region with a related diversity LQ value higher than 1 is assumed to be important for achieving positive externalities from cognitive proximity besides the theorised benefits of spatial proximity described in section 3.2.1.

4.2.2.1 Identifying Related Diversity

Selecting industries that are considered to be in *cognitive proximity* to 'Life Science and Health' sectors is based on branch-wise analysis of the standard hierarchical industry classification system used in the Netherlands (Neffke and Henning, 2010).

Presumably, beneficial higher levels of cognitive relatedness between firms in related industries are shared when those industries are more closely connected in this classification system, i.e. industries pertaining to the same higher-tier branch.

Even so, the precise theoretical grounds for investigating agglomeration economies with this approach is unclear. Yet, several scholars have been successful in using 'classification-based relatedness,' such as Boschma and Iammarino (2009) regarding Italy. This research will therefore investigate two alternative definitions regarding related diversity to attempt to account for this definition issue.
According to the Dutch statistics office, the Topsector 'Life Science and Health' is divided in three sub-sectors, each of course having its own subset of SBI 5-digits classification codes as shown in table 4.1.

Table 4.1 SBI.2008 Classification of Topsector 'Life Science and Health'

Subsector	SBI.2008 Classification	SBI.2008 Main Branch
Pharmaceuticals	21.10, 21.20	21
Medical Devices	26.60, 32.05	26, 32
Research & Development	72.112, 72.192	72

(Source: Centraal Bureau voor de Statistiek, 2012)

Set up as a hierarchical classification system, the leading SBI two digits indicate the main industry branch to which an industry pertains. Industries classified in the same branch are expected to benefit from positive externalities stemming from cognitive proximity between these industries (see section 3.2.3). The resulting list of related industries in connection to the 'Life Science and Health' Topsector definition is shown in appendix A.

The first definition will encompass the regions' number of jobs in related diversified industries in conjunction with the 'Life Science and Health' sectors for 2006. Following from the list in appendix A, it will encompass all 5-digits sectors that fall under the 2-digits higher-tier definition of which the 'Life Science and Health' sectors pertain as shown in table 4.1 above, i.e. SBI branches 21, 26, 32, and 72. The resulting variables LQ.JOB.RDFULL.6 and LQ.JOB.NUT.RDFULL.6 will thus denote the relative regional specialisation in related diversity.

The second definition, however, will be limited to a subset of related diversified industries to include only those industries sharing a two-digit branch code with the Research and Development subsector of the Topsector 'Life Science and Health,' i.e. the SBI 72 main branch (variable LQ.JOB.RDRSCH.6, LQ.JOB.NUT.RDRSCH.6, respectively). This variables will therefore denote the regional specialisation in related industries in connection with 'Life Science and Health' R&D sectors, so to attempt to find evidence for the importance of related knowledge-sharing for regional employment growth in 'Life Science and Health' sectors.

Notably, the 'Life Science and Health' sectors are omitted from these definitions of regional specialisation in related diversity, as LQ.JOB.LSH.6 will already account for the employment in the LSH sectors during analysis.

Finally, a rather arbitrary definition for related diversity as suggested by the Dutch Ministry of Economic Affairs is considered in this research as well. The rationale for selecting these industries is based on the close-knit linkages between firms active in 'Life Science and Health' and firms pertaining to two other Topsectors, namely: 'Agro and Food' and 'Hi-Tech Systems and Materials' (Centraal Bureau voor de Statistiek, 2013; Ministerie van Economische Zaken, 2011). Notably, these sectors are not selected through the notion of 'classification-based relatedness' as before.

The variables LQ.JOB.RDTOP.6 and LQ.JOB.NUT.RDTOP.6 will thus indicate the relative regional specialisation in 'Agro and Food' and 'Hi-Tech Systems and Materials' to investigate the impact on employment growth in 'Life Science and Health' sectors located in spatial proximity as well.

These alternative specifications for related diversity in this research will for convenience be referred to as 'Full,' 'Research,' and, 'Topsector.' Table 4.2 below provides an overview of the precise meaning of each specification.

Table 4.2 Alternative Definitions of Related Diversity Considered in this Research

Specification	Description
Full	All related sectors sharing the SBI two-digit main branches with all Topsector 'Life Science and Health' sectors
Research	Encompasses all sectors sharing the same SBI two-digit main branches with just the R&D subset of Dutch 'Life Science and Health'
Topsector	All sectors in Topsectors 'Agro and Food' and 'High-tech Systems and Materials'

4.2.3 Interaction Variables

Having regional specialisation in either 'Life Science and Health' sectors or related diversity may not be adequate to allow for improved knowledge-sharing per se, e.g. in the case of (in)formal collaborations. Provided regions are specialised in both 'Life Science and Health' and related industries, *cognitive proximity* may result in additional beneficial reciprocal effects. And so, an interaction variable is included to account for this potential additional effect.

The interaction variable is calculated for each geographical scale by multiplying the LQ in 'Life Science and Health' with that for each specification of related diversity at the corresponding geographical scale (variable LQ.INTRCT.JOB.RD.6 and LQ. INTRCT.JOB.NUT.RD.6).

4.2.4 Control Variables

Several control variables are also considered in this research to account for the influence of several aspects of the local business milieu, namely (1) population density; (2) labour force population; (3) number of university graduates; (4) average firm size; (5) average housing value; and, (6) proximity to a medical university.

Population density is used as a proxy to account for the level of urbanisation of any given region (variable POP.DENS.6). Urbanised regions are considered to support productivity growth in numerous ways (Porter, 2000), yet the connection between city size and productivity gains remains unclear. Smaller cities may be rather specialised allowing for Marshallian productivity gains, whereas larger cities may allow for increased production levels due to a higher degree of economic diversity (Farhauer and Kröll, 2011). Both mechanisms explicitly depend on labourers for the dissemination of local knowledge benefiting production (Boschma, 2009). Therefore, regional labour force (variable LAB.FORCE. REL.6; i.e. the relative share of people of working age) is also explicitly considered in this research.

To add to the theorised importance of the availability of employees, the relative share of university graduates for any given region is also included as a proxy for the regional education level (variable EDU.REL.6). Local availability of highly educated employees will theoretically ameliorate regional employment growth in R&D intensive 'Life Science and Health' sectors, as well as employment growth in related industries.

Following from section 2, several theories discuss to some degree the importance of the regional distribution of average firm size. Marshall (1920) and Chinitz (1961) suggest that a local milieu of small firms (fewer than 10 employees) is beneficial because of formal and informal connections providing (tacit) knowledge and many specialised services locally. Moreover, Porter (1990) argues that a diversified regional build-up of small firms is beneficial for the competitiveness of a cluster. As such, it seems sensible to attempt to account for the potential effect of the average firm size of 'Life Science and Health' firms on localised economic growth (variable AVG.FIRM. LSH.6).

Housing prices may be used as a proxy for the local (residential) quality, e.g. proximity to metropolitan area providing high-quality services, therefore, regional average housing price is also included as a control variable (variable HOUSE. VALUE.6).

The importance of proximity to a university for local knowledge spillovers has been corroborated by several studies (e.g. Anselin, et al. (1997) and can thus be considered a crucial endowment to any region (Goddard and Chatterton, 1999). For example, the occurrence of a university may trigger R&D investments indirectly (Jaffe, 1989), provided that this university is highly appraised (Laursen et al., 2011).

Identifying regions proximate to any of the several medical universities located in the Netherlands is done manually by the author. A dummy variable (variable DUMMY.UNI) indicates a first tier regional proximity to a medical university, i.e. conterminous municipalities (the locations of which are shown in figure 5.4).

4.3 Estimating Equations

Two different types of models will be tested in this research, each having a different dependent variable. And, because of the three alternative specifications regarding related diversity described in table 4.2, each model will be run three times resulting in a total of six sets of estimates.

Natural logarithm transformation will be used in order to do away with data skewness issues for the variable JOB.LSH.6, JOB.LSH.11 and HOUSE.VALUE.6.

Every variable is measured at the municipality level, unless the NUTS 3 level is explicitly indicated by use of the acronym 'NUT' in the variable name. The models are structured as follows:

$$
\begin{aligned}
Y = \quad & \beta_0 + \beta_1 \log(\text{JOB.LSH.6}) + \beta_2\, \text{LQ.JOB.LSH.6} + \beta_3\, \text{LQ.JOB.NUT.LSH.6} + \\
& \beta_4\, \text{LQ.JOB.RD.6} + \beta_5\, \text{LQ.JOB.NUT.RD.6} + \beta_6\, \text{LQ.INTRCT.JOB.RD.6} + \\
& \beta_7\, \text{LQ.INTRCT.JOB.NUT.RD.6} + \beta_8\, \text{POP.DENS.6} + \beta_9\, \text{LAB.FORCE.} \\
& \text{REL.6} + \beta_{10}\, \text{EDU.REL.6} + \beta_{11}\, \text{AVG.FIRM.LSH.6} + \beta_{12} \log(\text{HOUSE.} \\
& \text{VALUE.6}) + \beta_{13}\, \text{DUMMY.UNI} + e + C.
\end{aligned}
$$

The first type model, cf. *forecasting model*, is used to attempt to explain employment growth in the Dutch Topsector 'Life Science and Health' by using data from the base year 2006. As such, the dependent variable *Y* will equal DELTA.JOB.LSH, i.e. the difference in the regional level of jobs in LSH between 2006 and 2011. Put differently, the model will attempt to predict the current development in employment in 'Life Science and Health' industries by using data from 2006, whilst compensating for the level of employment in 'Life Science and Health' in the base year by including the variable log(JOB.LSH.6) which denotes the natural logarithm of JOB.LSH.6.

The second type model, cf. *level model*, is used to attempt to explain the level of employment in 'Life Science and Health' sectors in 2011 by using data from base year 2006. As such, the dependent variable Y will equal log(JOB.LSH.11) which denotes the natural logarithm of the variable JOB.LSH.11. Compared to the forecasting model, the level model will compensate for the level of jobs slightly differently. Whilst Y in this model does not include the level of employment in 'Life Science and Health' sectors in base year 2006, potentially a large part of the explanatory power of the model will be captured by the variable log(JOB.LSH.6). Whatever variance remains for the model to be explained will subsequently be captured by the remaining variables included in the level model.

4.4 Descriptive Statistics

This section provides an overview of the descriptive statistics of all variables used for the estimating equations as shown in table 4.1 below. All variables are measured at the smaller municipality level, unless the NUTS 3 geographical level is explicitly specified by use of the abbreviation 'NUT.'

Table 4.1: Simple statistics of the Regression Sample

Variable	N	Min.	Max.	Mean	Std. Dev.
DELTA.JOB.LSH	415	-1714	535	0,822	105,827
log(JOB.LSH.6)	415	0,690	8,600	1,278	2,009
log(JOB.LSH.11)	415	0,690	8,220	1,418	2,064
LQ.JOB.LSH.6	415	0	36,995	0,758	3,587
LQ.JOB.NUT.LSH.6	415	0	8,162	0,613	1,265
LQ.JOB.RDFULL.6	415	0	10,534	0,791	1,131
LQ.JOB.NUT.RDFULL.6	415	0	3,686	1,026	0,523
LQ.JOB.RDRSCH.6	415	0	37,181	0,727	3,428
LQ.JOB.NUT.RDRSCH.6	415	0	13,970	0,737	1,235
LQ.JOB.RDTOPS.6	415	0,232	3,972	1,371	0,676
LQ.JOB.NUT.RDTOPS.6	415	0,487	3,051	1,057	0,305
INTRCT.LQ.RDFULL.6	415	0	57,076	0,710	3,862
INTRCT.LQ.NUT.RDFULL.6	415	0	9,940	0,635	1,355
INTRCT.LQ.RDRSCH.6	415	0	144,374	0,939	9,237
INTRCT.LQ.NUT.RDRSCH.6	415	0	15,050	0,517	1,642
INTRCT.LQ.LSH.RDTOPS.6	415	0	38,182	0,832	4,061
POP.DENS.6	415	24	5770	773,853	952,374
LAB.FORCE.REL.6	415	0,648	0,754	0,637	0,130
EDU.REL.6	316	6,882	51,877	15,635	5,479
AVG.FIRM.LSH.6	221	1	2593	42,886	206,763
log(HOUSE.VALUE)	399	4,770	6,340	5,367	0,240
DUMMY.UNI	415	0	1	0,110	0,311

4.5 Outlier Analysis

Based on the 'Outlier Labelling Rule' (Hoaglin et al., 1986), Hoaglin and Iglewicz (1987) suggest a multiplier value of g=2.20 to denote the range, cf. minimum and maximum value, for indicating outliers. Basically, multiplying the difference between the value of the first and third quartile raw score of any variable gives the value g'. The minimum value is then calculated by subtracting g' from the first quartile raw score. Subsequently, the maximum value is calculated by adding g' to the third quartile raw score. Any cases falling outside this range is considered an outlier.

Using this method, several municipalities are found to be outliers. Most strikingly, the municipality of Oss is highly specialised resulting in having one of the highest locational quotients for 'Life Science and Health' sectors, namely 32.8 for base year 2006. Even a decline of 1714 jobs in just 5 years due to the closing of a key firm, an extreme value in itself in this dataset, changed the locational quotient for the Topsector to 24.6 in 2011, ranking Oss in the top 5 of most specialised in 'Life Science and Health' municipalities in this dataset for that same year.

Another striking outlier is Amsterdam which has a gross growth in 'Life Science and Health' jobs of 535 between 2006 and 2011, yet the number of firms in that same sector increased by just 3 during that same period.

Leiden is shown to be an outlier when considering the difference in number firms at the municipality level for the period 2006-2011. Leiden's increase of 25 firms in the 'Life Science and Health' sector is more than double that of the second highest growing municipality in that respect, i.e. Maastricht with an increase of 11 firms over that same period.

However, as clusters in 'Life Science and Health' are so sparsely in the Netherlands (see figure 5.4 in section 5.1.3), not considering these outliers would severely reduce the relevance of the regression estimates in connection to the Dutch firm population. Therefore, outliers are included in the analysis.

4.6 Limitations

4.6.1 Data Limitations

This research is limited to just using data regarding the Dutch national establishment firm population. And therefore, any exogenous effects, e.g. the influx of FDI, are not considered here. But of course, such effects may very well be captured indirectly in the data.

Moreover, extra-regional trade linkages and spillovers are not investigated as well, even though such effects may indeed also positively contribute to the local (related) knowledge pool (Boschma and Iammarino, 2009), at least in cases where such ties are not too rigid in order to avoid negative lock-in (Grabher, 1993).

However, by also considering the broader NUTS 3 geographical scale for specialisation in both 'Life Science and Health' and related industries in this research, extra-regional spillover effects may to some extent be captured by the data, although there are of course more sophisticated approaches for doing so.

The LISA dataset employed in this research has shown a steady growth in jobs and firms in 'Life Science and Health' industries since 1996, despite the current global economic recession (Ministerie van Economische Zaken, 2013). Consequently, the strength of any effects following from this research may be compromised.

Data quality may differ among provinces as the responsible provincial chambers of commerce may not always prioritise collecting regional employment data over other tasks.

4.6.2 Employment Data

Employment data is used in this research, even though using firm data would appear equally sensible. But firm data is rather steady over shorter periods of time, and lacks the dynamic nature employment data does have. Particularly, when considering that labour mobility allows for skill-related knowledge transfers to take place between related diversified industries, it makes sense to use employment data (Neffke and Henning, 2010).

4.6.3 Identifying Related Diversity

Branch-wise analysis of the Dutch standard hierarchical industry classification system for identifying related industries in this research is not without difficulties (Neffke and Henning, 2010). In particular, there is so far no clear theoretical justification for using this method (Frenken et al., 2007). Therefore, industries' *relatedness* may in some cases appear rather arbitrary, and may lack any theoretical foundation as to why such industries can be considered having shared competences.

Operationalising such an approach, however, is rather straight-forward and several scholars have in fact been successful using this method, see e.g. Boschma and Iammarino (2009).

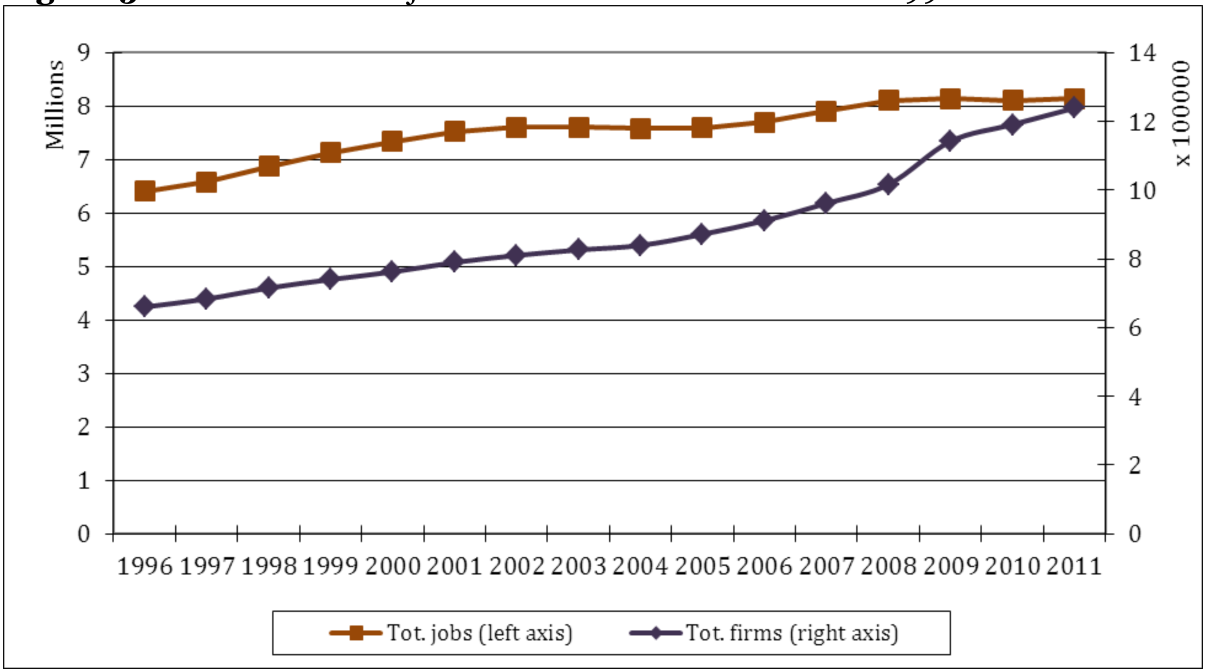
Additionally, several industries pertaining to the Topsector 'Life Science and Health' may very well not rely on local related knowledge, e.g. when firms are in advanced product-cycle stages (Vernon, 1960; 1966). Even so, these industries are explicitly taken into account in this research.

5 Models and Results

5.1 Trends in Dutch Economy

Figure 5.1 below shows the overall growth in total number of jobs and firms in the Netherlands between 1996 and 2011. However, as of 2009 employment growth has stagnated as a result of the current global economic recession (Centraal Bureau voor de Statistiek, 2012; 2013). Strikingly, the growth in total number of firms has actually increased as of 2009. Most likely, unemployment will trigger people into self-employment as part of today's ongoing changes to the economic structure.

Figure 5.1 Total number of jobs and firms in the Netherlands 1996 - 2011



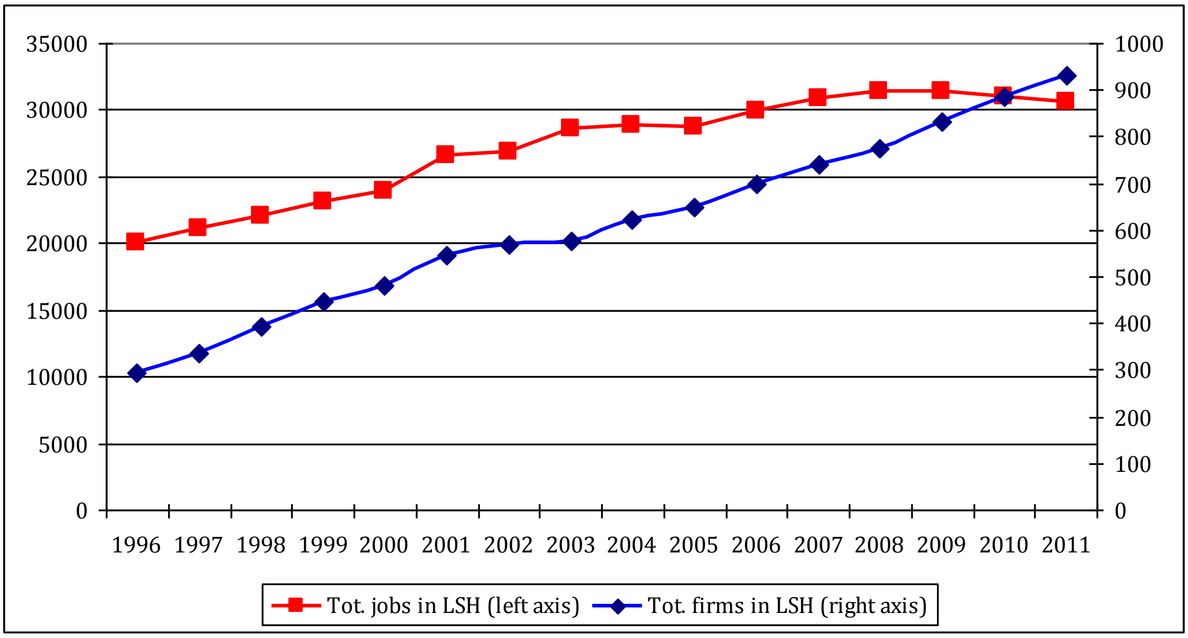
(Source: LISA, 1996 – 2011)

5.1.1 Trends in 'Life Science and Health'

Following from figure 5.2 below, employment in Topsector 'Life Science and Health' has shown an annual average growth rate of 3.5% during the period 1996 to 2011, nearly double that of the entire Dutch economy. Similarly, the annual average national growth rate of the number of firms in 'Life Science and Health' sectors is substantially higher than the national annual average growth rate as well, namely 14.3% and 5.8%, respectively.

Parallel to the development of the overall Dutch economy discussed above, the positive effect of unemployment on the growth of the number of firms during economic decline, is also taking place in Topsector 'Life Science and Health' sectors as of 2009 (see figure 5.2). Again, unemployment may trigger people into founding new businesses or enter into self-employment. And because of their existing skill-set, those new start-up will most likely be in similar, or at least *cognitively proximate* related sectors (Klepper, 2007), benefiting the region (Boschma, 2009).

Figure 5.2 The total number of jobs and firms in the Dutch LSH sector 1996-2011

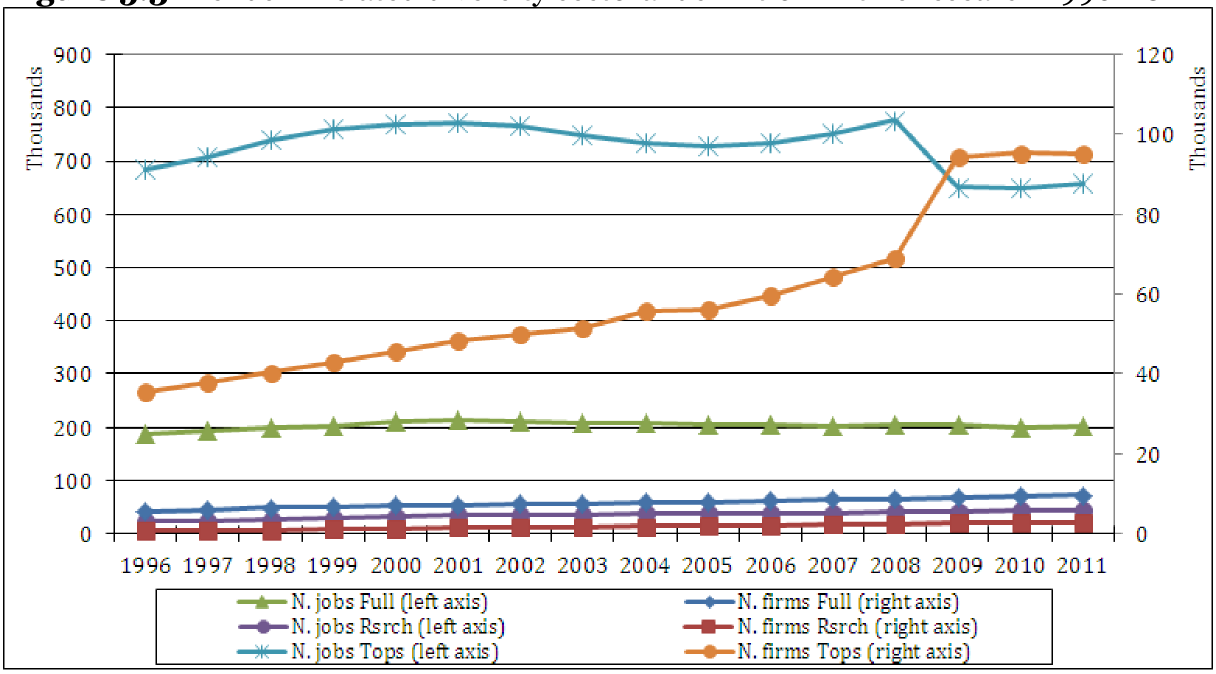


(Source: LISA, 1996 – 2011)

5.1.2 Trends in Related Industries

Figure 5.3 illustrates the development of the national total number of jobs and firms for all three specifications of related diversity used in this research. Notably, the general trends in the Dutch economy as discussed in section 5.1.1, are not evident in the development of these sets of industries.

Figure 5.3 Trends in related diversity sectoral definition in this research 1996-2011



(Source: LISA, 1996 – 2011) 'Full,' 'Rsch,' and 'Tops' denotes related diversity specifications 'Full,' 'Research,' and 'Topsector,' respectively.

Following from figure 5.3, the development of employment and number of firms for each specification of related diversity used in this research is shown to be rather steady during the period 1996 and 2011, expect for the 'Topsector' specification, i.e. sectors pertaining to either the Topsector 'Agro and Food' or 'Hi-Tech Systems and Materials.'

Rather, the progression in employment in the 'Topsector' specification for related diversity shows a dynamic development pattern. This may be the result of a definition problem resulting from the sheer size of this specification encompassing substantially more jobs than the other two specifications. As such, many intertwined effects may be at play simultaneously resulting in this rather erratic development path. Also, it may indicate a strong susceptibility to the economic climate for this set of industries.

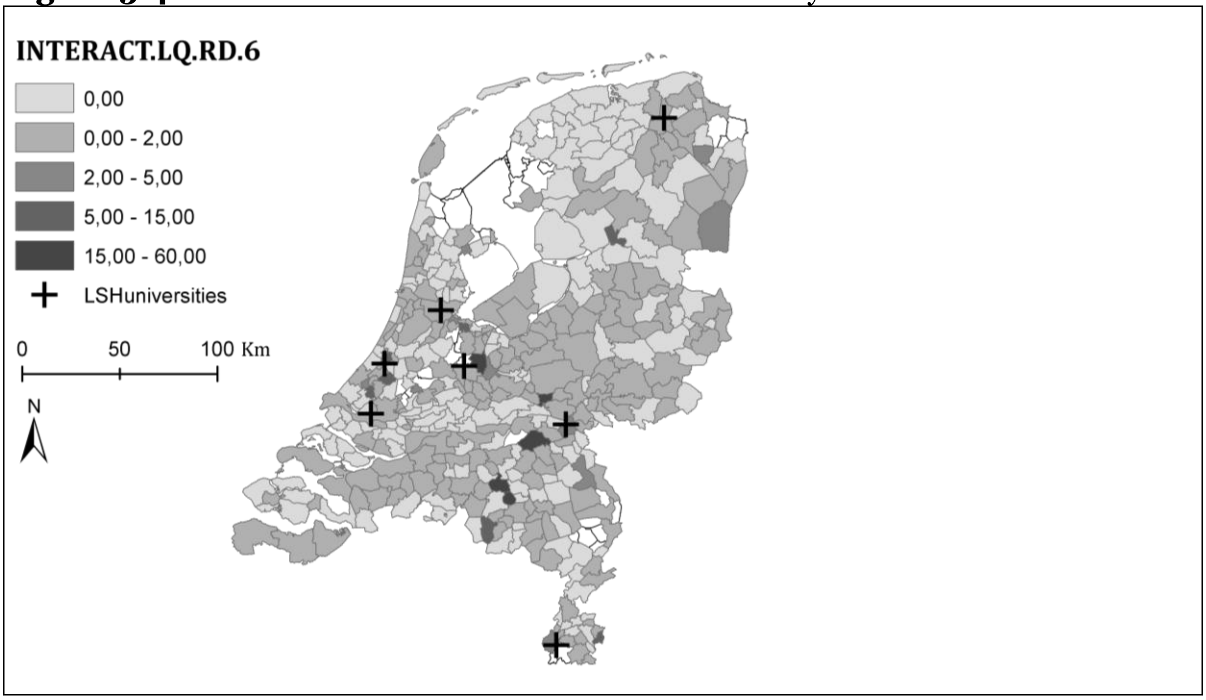
Yet, the sudden drop in employment in 2009, and opposite rise in number of firms for the 'Topsector' specification in the same year, may be the result of changes made to the sectoral definition of the SBI-2008 classification system as of 2008, although our data are corrected for said change.

5.1.3 Geography of 'Life Science and Health' and Related Industries

Figure 5.4 below illustrates the interaction variable between the Topsector 'Life Science and Health' and the 'Full' specification of related diversity at the municipality level. In other words, the map highlights those municipalities that are specialised in both 'Life Science and Health' and related diversity.

From this map it is obvious that the total number of locations we will expect positive related knowledge externalities to arise, is rather scarcely in the Netherlands.

Figure 5.4 Life Science and Health and Related Diversity in the Netherlands



(Source : LISA, 2006)

5.2 Regression Analysis

5.2.1 Forecasting Model

The first model in this research will attempt to predict regional growth in employment in Topsector 'Life Science and Health' sectors by using firm data from base year 2006. As discussed in section 4.3, the dependent variable for this model is DELTA.JOB.LSH, i.e. the difference in employment in 'Life Science and Health' between 2006 and 2011.

Essentially, the model is used to attempt to disentangle the positive externalities linked to regional specialisation in both 'Life Science and Health' and the related industries thereto, and, the expected additional interaction effect between them.

Two subsequent geographical scales are tested to account for issues with correctly defining the precise spatial boundaries of any clustered region (Porter, 2000).

The model has been run three times, to account for each specification of related diversity used in this research.

To recap section 4.2.2, firstly, the 'Full' specification encompasses all related diversified industries hierarchically connected to the full Topsector 'Life Science and Health' sectoral definition. Secondly, the 'Research' specification is limited to related industries sharing SBI two-digit branches with the R&D subset in 'Life Science and Health' sectors. Lastly, the 'Topsector' sectoral specification of related diversity comprises industries pertaining to either the Topsector 'Agro and Food' or 'High-Tech Systems and Materials' (Centraal Bureau voor de Statistiek, 2012).

A total of only 196 cases, cf. roughly half of the 415 municipalities in the Netherlands, are included in this model due to an unfortunate combination of missing values in several variables. Following from the regression estimates in table 5.1, all three specifications perform rather well in this forecasting model, having R-squared values of 0,559; 0,397; and 0,405, respectively.

Table 5.1 Model 1 Regression Estimates

Variable	Full	Research	Topsector
Constant	-646,329 (419,283)	-225,754 (465,212)	-322,320 (462,006)
log(JOB.LSH.6)	9,468** (4,627)	10,545** (5,487)	6,119 (5,449)
LQ.JOB.LSH.6	-1,681 (3,477)	-33,544*** (3,462)	-57,662*** (6,195)
LQ.JOB.NUT.LSH.6	-9,251 (13,800)	-3,521 (7,000)	-26,724 (22,585)
LQ.JOB.RDFULL.6	25,696*** (8,046)		
LQ.JOB.NUT.RDFULL.6	5,064 (19,088)		
LQ.INTRCT.JOB.RDFULL.6	-25,251*** (2,378)		
LQ.INTRCT.JOB.NUT.RDFULL.6	9,304 (12,887)		
LQ.JOB.RDRSCH.6		-8,361*** (2,922)	

LQ.JOB.NUT.RDRSCH.6		-11,037 (12,901)	
LQ.INTRCT.JOB.RDRSCH.6		5,555*** (,957)	
LQ.INTRCT.JOB.NUT.RDRSCH.6		11,161 (6,913)	
LQ.JOB.RDTOPS.6			-5,550 (20,802)
LQ.JOB.NUT.RDTOPS.6			-35,658 (33,040)
LQ.INTRCT.JOB.RDTOPS.6			27,286*** (4,541)
LQ.INTRCT.JOB.NUT.RDTOPS.6			19,849 (18,469)
POP.DENS.6	-3,181E-005 (,008)	,002 (,010)	,008 (,010)
LAB.FORCE.REL.6	502,429 (384,431)	183,111 (450,401)	259,473 (445,159)
EDU.REL.6	4,100*** (1,541)	1,062 (1,844)	3,151* (1,762)
AVG.FIRM.LSH.6	,208*** (,057)	,406*** (,069)	,432*** (,069)
log(HOUSE.VALUE.6)	39,892 (47,476)	15,766 (51,662)	26,176 (53,802)
DUMMY.UNI	38,841 (24,248)	34,536 (28,568)	56,616** (28,401)
R-squared	,559	,397	,405
Adj. R-squared	,528	,354	,363
F	17,879***	9,270***	9,587***

Dependent variable: DELTA.JOB.LSH. N = 196. Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

The regression coefficients for the level of jobs in base year 2006, variable JOB. LSH.6, is only significant for the ‘Full’ and ‘Research’ specifications of related diversity, at the 95% confidence level. The sign of these estimates is positive, which of course is in line with our expectation of path dependency in job creation. In other words, jobs in the same sector are more easily created in (new firms in proximity to) existing firms, rather than by creating such jobs haphazardly in the Netherlands.

Lacking a significant result for the level in jobs in the ‘Topsector’ specification does not seem logical. But, as figure 5.3 above illustrates that the total number of jobs for the ‘Topsector’ specification of related diversity fluctuates over time, several effects will be at play simultaneously. This may indeed impede calculations towards a fitting coefficient for this variable.

Regional specialisation in ‘Life Science and Health’ sectors is measured at both the municipality level, and the NUTS 3 level (variable LQ.JOB.LSH.6, and LQ.JOB.NUT. LSH.6) to attempt to discern the spatial ‘reach’ up to which clusters induce improved employment growth in ‘Life Science and Health’ sectors.

Significant results are only reported at the smaller geographical scale, and, at the highest confidence level. Remarkably, however, the coefficients for LQ.JOB.LSH.6 are negative, suggesting a diminishing effect of regional specialisation in 'Life Science and Health' on same-sector employment growth. This is at odds with our expectation.

To see if regional specialisation has been captured by the level of employment to some degree, the forecasting model has also been tested without correcting for this scale effect, as well as using the natural logarithm of the dependent variable DELTA.JOB.LSH, which did not change this unexpected result.

As mentioned above, our data suggest that the level of jobs in base year 2006 does have a significant, positive effect on employment growth. Taken together, it suggests that – rather than the relative share – the mere size of regional employment in 'Life Science and Health' contributes positively to employment growth in these industries.

To attempt to find evidence for the theorised beneficial effects of knowledge-sharing between 'Life Science and Health' sectors and related industries, the level of regional specialisation in related industries at both geographical scales is included in the forecasting model as well (variable LQ.JOB.RD.6, and LQ.JOB.NUT.RD.6).

Significant results are reported at the highest confidence level for the 'Full' and 'Research' specifications of related diversity, and only at the municipality level.

Remarkably, the sign of these coefficients are different. Whereas related industries in the 'Full' specification are shown to have a positive effect on employment growth in 'Life Science and Health' sectors, having regional 'Research' related industries appear to have a diminishing effect on said employment growth. A reasonable explanation for this unexpected latter result is lacking.

Having regional specialisation in either 'Life Science and Health' sectors or related diversity may not adequately allow for related knowledge-sharing *per se*. Besides the baseline effects discussed above, we expect to find additional beneficial reciprocal effects when both types of industries collocate regionally. And so, the interaction between both sets of industries is investigated at both geographical levels for every specification of related diversity in this research (variable LQ.INTRCT.RD.6, and LQ. INTRCT.NUT.RD.6).

The model yields significant results for all three specifications of related diversity at the lower geographical level. It is encouraging that, although the 'Full' specification coefficient for the interaction effect is negative, the coefficient sign of both the 'Research' and 'Topsector' specification of related diversity is in fact positive.

Thus, our data do support the notion that local related knowledge-spillovers between 'Life Science and Health' firms and related industries, in particular, are important for gaining employment growth at specialised regions in 'Life Science and Health' during the period 2006 to 2011.

The variable POP.DENS.6, i.e. municipal population density, is included as a proxy for the level of urbanisation at the municipality level in this research. To particularise the level of urbanisation, the variable HOUSE.VALUE.6 has been included at the same geographical scale to attempt to account for the local (residential) quality of the living environment.

Both variables, however, have no significant impact on regional employment growth in Topsector 'Life Science and Health' sectors, following from our data during the period 2006 to 2011. This finding may not be unexpected as urbanisation economies are primarily linked to diversified sectoral structures of a local economic system, whereas 'Life Science and Health' firms are assumed to cluster spatially to benefit from Marshallian agglomeration externalities, such as related knowledge.

Also included in the forecasting model, is the variable LAB.FORCE.REL.6, i.e. the relative share of people of working age of the total number of inhabitants of a municipality. And, to particularise the availability of workers, variable EDU.REL.6 is also included to account for the expected demand for highly-educated workers in the knowledge-intensive Topsector 'Life Science and Health.' The share of available workers did not yield any significant results, the relative number of university graduates did. Both the 'Full' and 'Topsector' specification of related diversity show positive, significant coefficients, but only at the 90% confidence level for the latter.

Unexpectedly, our data do not show significant, positive, results for the 'Research' specification in this respect, as the 'Research' specification for related diversity is by definition highly knowledge-intensive. A plausible explanation is lacking.

For each variant of the forecasting model, the variable AVG.FIRM.LSH.6, i.e. regional average size of 'Life Science and Health' firms, demonstrates significant, positive coefficients at the highest confidence level. This implies that a *de facto* increase in average firm size advances employment growth in 'Life Science and Health' sectors during the period 2006 to 2011, although there will be a limit to this effect. One explanation is, of course, that larger firms have more resources readily available to be able to hire new staff quickly in response to e.g. changing market demands (Chinitz, 1961). Notably, the regional average firm size has also been tested, which did not yield significant results, and was therefore omitted from the models.

To attempt to find evidence of the positive externalities resulting from (in)formal collaborative networks (Boschma, 2009), a dummy variable DUMMY.UNI is included to indicate regions in proximity to a Dutch medical university, the locations of which are depicted in figure 5.4 above.

Only for the 'Topsector' specification of related diversity in the forecasting model, a positive, significant, coefficient is reported, at the 95% significance level.

This appears to suggest that related collaborative networks are more important than the availability of skilled workers, at least for the 'Topsector' specification of related diversity.

Conversely, our data suggest that in the 'Full' specification of related diversity, the regional availability of skilled workers trumps firms engaging in (in)formal networks and collaborations with a proximate medical university, for attaining employment growth in 'Life Science and Health' industries. One explanation may be that in this case the educational level of workers is valued more by employers, than employees having appropriate knowledge one will have learned attending a medical university.

The lack of significant results for the 'Research' specification of related diversity in this respect is unexpected, as industries pertaining to this sectoral classification are by definition involved in innovative activities, and, are assumed to rely heavily on local related knowledge.

5.2.2 Level Model

The second model employs as its dependent variable the natural logarithm of JOB. LSH.11 to attempt to predict the level of employment in 2011 by using firm data from base year 2006.

Following from table 5.2 below, the second model has been run three times as well, each employing an alternative specification of related diversity used to calculate the interaction variable LQ.INTRCT.RD.6. These models include the same 196 cases as are used in the previous model, and every variations of the second model perform substantially better, having R-squared values of 0,816 and beyond.

Table 5.2 Model 2 Regression Estimates

Variable	Full	Research	Topsector
Constant	-4,281 (4,059)	-4,682 (3,856)	-5,566 (3,771)
log(JOB.LSH.6)	,841*** (,045)	,843*** (,045)	,817*** (,044)
LQ.JOB.LSH.6	,033 (,034)	-,003 (,029)	-,044 (,051)
LQ.JOB.NUT.LSH.6	,022 (,134)	-,032 (,058)	-,493*** (,184)
LQ.JOB.RDFULL.6	-,020 (,078)		
LQ.JOB.NUT.RDFULL.6	-,064 (,185)		
LQ.INTRCT.JOB.RDFULL.6	-,026 (,023)		
LQ.INTRCT.JOB.NUT.RDFULL.6	-,035 (,125)		
LQ.JOB.RDRSCH.6		-,021 (,024)	
LQ.JOB.NUT.RDRSCH.6		,000 (,107)	
LQ.INTRCT.JOB.RDRSCH.6		,007 (,008)	
LQ.INTRCT.JOB.NUT.RDRSCH.6		,033 (,057)	
LQ.JOB.RDTOPS.6			-,297 (,170)
LQ.JOB.NUT.RDTOPS.6			-,166* (,270)
LQ.INTRCT.JOB.RDTOPS.6			,046 (,037)
LQ.INTRCT.JOB.NUT.RDTOPS.6			,392** (,151)
POP.DENS.6	3,919E-005 (,000)	4,321E-005 (,000)	5,096E-005 (,000)
LAB.FORCE.REL.6	8,615*** (3,722)	8,502** (3,733)	7,774** (3,634)
EDU.REL.6	,015 (,015)	,013 (,015)	,016 (,014)
AVG.FIRM.LSH.6	,000	,000	,000

	(,001)	(,001)	(,001)
log(HOUSE.VALUE.6)	-,221 (,460)	-,146 (,428)	,219 (,439)
DUMMY.UNI	,142 (,235)	,079 (,237)	,146 (,232)
R-squared	,816	,816	,823
Adj. R-squared	,803	,802	,811
F	62,488***	62,242***	65,658***

Dependent variable: log(JOB.LSH.11). N = 196. Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

However, far fewer variables show significance in this model compared to the forecasting model. For each specification of related diversity used in this research, only the natural logarithm of the variable JOB.LSH.6, i.e. the level of jobs base year 2006, and the relative labour force variable LAB.FORCE.REL.6 show significant, positive coefficient at the 95% and 90% confidence level.

Additionally, for the 'Topsector' specification model variant, regional specialisation in both 'Life Science and Health,' as well as related industries demonstrate negative, significant coefficients at the NUTS 3 geographical scale. Also, our data indicates a positive, significant coefficient at for the interaction effect between 'Life Science and Health' sectors and industries pertaining to the 'Topsector' specification of related diversity at that same geographical scale.

This is at odds with the findings from the first model, which demonstrates significant results exclusively at the municipality level (see table 5.1). Apparently, linkages between 'Life Science and Health' firms and other Topsectors are not strongly geographically bounded as are the 'Full' and 'Research' specifications of related diversity, because our data does not indicate similar results for the other two specifications of related diversity in the level model.

5.2.3 Ancillary Modeling

To account for the novelty in operationalising related diversity research (Frenken et al., 2007), an alternative approach for investigating the regional interaction between Topsector 'Life Science and health' sectors and related diversity has been tested as well. Essentially, Boschma and Iammarino (2009) suggest calculating the level of entropy between (sets of) industries collocating in the same region (see for details appendix B). The models using the level of entropy to investigate said interaction, show very similar results compared to the models using the interaction variable used above. However, the entropy measure is not as straight-forward to interpret and induces additional missing values due to the way it is calculated, and so, this approach is omitted from the results.

Furthermore, the models in this research have been repeated using firm data as well. Yet, this did not yield any additional insights. One reason may be that the total number of firms is rather stable over shorter time periods compared to employment data, which may limit the explanatory power of the models.

Moreover, the importance of labour for disseminating or indeed retaining, local, unique (tacit) knowledge has been suggested in connection to innovative behaviour in section 3.1.2. The notion of related diversity adds to these arguments the skill set of workers' previous capacity, result in strong inter-industry labour flows between *cognitively* related industries (Neffke and Henning, 2010). Therefore, it seems reasonable to prefer using employment data in this research.

In closing, the strongest outlier, cf. the municipality of Oss, has been excluded from our dataset to examine its impact on the results. Although the regression estimates are lowered for all models, the coefficients remain at the same confidence level, and, the sign of the coefficients is unchanged.

As clusters in 'Life Science and Health' sectors are so sparsely in the Netherlands, not considering the municipality of Oss would severely reduce the explanatory power of the models in connection to the Dutch firm population. Therefore, outliers have been included in this research.

6 Discussion

6.1 Employment Growth at Specialised Regions

As described in section 3.3, several hypotheses have been suggested in order to structure this research. The first hypothesis posits that employment growth in Dutch 'Life Science and Health' clusters is higher compared to employment growth in lesser specialised regions in the same sectors during the period 2006 to 2011.

Following from section 3.1, the basic line of argument is that locating at a cluster provides firms with a distinct competitive advantage (Porter, 2000), as clusters allow for localised increasing returns to scale, improving the success rates of firms located there (Krugman, 1991). These positive externalities stem from improvements in the productivity of local firms, innovative behaviour, and, new local start-ups and spin-offs (Porter, 2000).

Yet, our data do not support the first hypothesis. Path dependency in job creation is shown to positively contribute to employment growth in 'Life Science and Health' sectors as a mere scale effect of clustering. This is underscored by the importance of greater average firm size in 'Life Science and Health' sectors following from our data.

However, the results indicate that regional specialisation in itself has in fact a diminishing effect on employment growth in 'Life Science and Health' sectors during the period 2006 to 2011. This seems highly unlikely, given that industrial clustering is so common in the economic landscape (McCann, 2001). Besides the effect of negative lock-in (Grabher, 1993), clustering may also be the result of regional specialisation in related industries. Also, the current global economic recession may overshadow any expected beneficial effects.

It is unfortunate that the current global economic recession has been captured in the time frame of our analysis. The 'Topsectoren Beleid' has specifically taken into account only those sectors having strong growth potential, possibly even during economic downturn (Ministerie van Economische Zaken, 2011). Indeed, employment in Topsector 'Life Science and Health' sectors has been growing during the period 2006 to 2011, albeit reduced as of 2010 and onwards.

One plausible explanation is that these highly innovative industries are particularly vulnerable to economic shocks, e.g. direct employment loss from budget cuts in high-quality research facilities. Although this does not appear in the overall development in employment in 'Life Science and Health.'

Moreover, our data support the importance of regional availability of highly-educated labour, even when proximity to a medical university does not seem to positively add to regional employment growth in 'Life Science and Health.' One explanation may be that in such cases the educational level of workers is more appraised by employers, than employees having the appropriate knowledge one will have learned attending a medical university and then look for employment nearby (Klepper, 2007).

As such, our data suggest that Marshallian regional knowledge-spillovers are important for attaining employment growth in 'Life Science and Health' sectors during the period 2006 to 2011. In fact, the lack of evidence for any unrelated inter-sectoral spillovers (Glaeser, et al., 1992) in this research, is not entirely unexpected.

Urbanisation economies are primarily linked to the diversified sectoral structure of a local economic system, whereas 'Life Science and Health' firms are presumed to cluster geographical in order to benefit from *inter alia* local (tacit) intra-industry knowledge-sharing (Marshall, 1920). This finding is at odds with the suggestions made by, e.g. Porter (1990), regarding the importance of urbanised areas for the (informal) exchange of information and knowledge.

6.2 Reciprocal Benefits of Related Industries

As discussed in section 3.2.3, related diversity has recently been proposed as an alternative mechanism for improving the competitiveness of an industrial cluster. To expand on the benefits of spatial proximity, the basic line of reasoning is that some commonality in skills and routines is needed to allow firms to successfully exploit the relevant local inter-sectoral knowledge to their advantage (Nooteboom, 2000). Such regional dissemination of related knowledge builds on local assets through the mechanisms of spinoffs, labour mobility, and efficient networking (Boschma, 2009).

To attempt to find evidence of such related knowledge externalities, the second hypothesis posits that employment growth at Topsector 'Life Science and Health' clusters develops in parallel with employment growth in related industries located at said clusters as well.

Our data support the second hypothesis when including all related industries of Topsector 'Life Science and Health' sectors through branch-wise analysis of the Dutch industrial classification system (Boschma and Iammarino, 2009). As such, this finding indicates that labour mobility is in fact an important mechanism in spreading related knowledge regionally, whilst building on local assets.

However, the positive effect of regional co-occurrence of related industries on employment growth in 'Life Science and Health' is lacking for any alternative specifications of relatedness used in this research. Again, this may be due to the global economic recession during the time frame of this research. But, several additional effects will be captured in these findings as well.

Identifying related industries may at times seem arbitrary, and lacking theoretical justification as to why to include certain industries as well (Frenken, et al., 2007).

Moreover, it can also be the result of an arbitrarily broadened, politically more favourable, sectoral definition of the Topsectors to artificially increase the relevance of said industries.

Resulting from the notion of *proximity paradox* (Boekel and Boschma, 2012), these results may also indicate that some related industries share too much cognitive proximity, which may result in negative lock-in because firms remain unaware of advancements in production inputs, which local competitors will in fact be able to exploit in order to gain a competitive advantage (Boekel and Boschma, 2012; Grabher, 1993; Nooteboom, 2000).

6.2.1 Linkages between Subsequent Topsectors

Alternatively, the third hypothesis posits that employment growth at Topsector 'Life Science and Health' clusters develops in parallel with employment growth in firms pertaining to the Topsectors 'Agro and Food' and 'High-tech Systems and Materials' collocating there. Research has shown that these Topsectors can be considered

related industries resulting from close linkages between them (Centraal Bureau voor de Statistiek, 2012).
One interpretation of our data may support the notion of the importance of efficient networking to employment growth in 'Life Science and Health' sectors, during the period 2006 to 2011. Although, of course, myriad effects will be at play simultaneously. Of course, this is along the lines of our expectations, especially when considering that Topsector industries are particularly selected by the government because of their innovative, knowledge-driven nature, which implies the need for high-quality networking.

Collaborative networks appear to primarily take place as a substitute for attaining relevant knowledge in regional proximity. In cases where firms pertaining to different Topsectors engage in collaborative networks, the positive effect on employment growth in 'Life Science and Health' sectors take place at the NUTS 3 geographical scale. This finding seems to suggest that collaborative networks are not bounded geographically to any municipal region *per se*, and, as such, there may be a certain *looseness* in such ties.

This finding also suggests that there is no risk of the *proximity paradox* (Boekel and Boschma, 2012) at play between these Topsector industries. Perhaps these sectors are cognitively not too far apart, yet, not too closely related either. This will give such firms some freedom in establishing (in)formal networks in alternative sectors, so to take in any knowledge externalities whenever there is a need of such specific knowledge, without hinging too strongly on just a few sectors.

Notably, proximity to a medical university is also shown to be beneficial to employment growth in 'Life Science and Health' clusters, which underscores the importance of having myriad knowledge-intensive collaborations.

So, even though these linkages are not easily identified through, e.g. branch-wise analysis of a standard hierarchical industry classification system, as is the case with hypothesis two, evidence of the beneficial effects of related diversity may be identified in all sorts of sets of industries.

6.3 Knowledge-Sharing Networks

The fourth hypothesis in this research posits that employment growth in 'Life Science and Health' clusters depends on the presence of the R&D subset of 'Life Science and Health' sectoral definition, as well as subsequent related diversified industries.

To build on the arguments in section 6.1 and 6.2, here we attempt to further disentangle the beneficial effects of knowledge-sharing networks from other local factors, by explicitly considering the role played by knowledge-intensive sectors, such as research facilities and medical universities.

To recap section 3.2.2, collocating with *academic incubators* provides innovative entrepreneurs, cf. spinoffs, with diverse collaborative networks at an early production stage (Schwartz and Hornych, 2010). This will compensate for the lack of crucial connections new firms need in order to be successful in the long run, as academic spinoffs will be highly dependent on local external information sources (Lorenzoni and Ornati, 1988).

Although regional specialisation for the R&D specification of related diversity did not yield the expected positive result, the coefficient for the additional interaction effect between both sets of industries has the expected positive sign. As such, our data confirm the importance of having access to local, diverse, collaborative networks on employment growth in 'Life Science and Health' sectors, during the period 2006 to 2011.
Moreover, it is only when we particularise related industries hierarchically connected to the Topsector 'Life Science and Health' to only include the knowledge-intensive R&D subset of industries, that we find evidence for the theorised benefits of related knowledge-sharing between cognitively proximate industries, in addition to spatial proximity.

6.4 Ancillary Interpretations

As briefly mentioned before, our data consistently shows that larger average firm size in 'Life Science and Health' sectors, is beneficial for employment growth in the same sectors. Several scholars have suggested the importance of the regional firm size distribution in this respect.

According to Scott (1988), clusters with a firm size distribution strong in SMEs are a prerequisite of successful innovative behaviour, because these new industrial areas support the necessary close interaction of social, political, and economic relationships (Porter, 1990; Rogerson, 1993). Notably, the overall regional firm size distribution is not considered in this research, thus, our results appear to only indirectly corroborate this viewpoint.

Clusters are geographically bounded, limited by rising spatial distance transactions costs, such as transportation costs and communications costs, which diminishes net profits (Krugman, 1993). And, the geographical boundaries of a cluster are hard to define accurately, as the spatial scope can range from a city up to and across national borders (Porter, 2000).

So, we have measured regional specialisation at two subsequent geographical scales to attempt to account for this definition issue. The lack of statistical evidence for the larger NUTS 3 level in our data suggests that 'Life Science and Health' clusters are highly spatially bounded, although the data used in this research does not allow measuring this effect beyond the municipality level.

The one exception is when we consider the *relatedness* between 'Life Science and Health' and two subsequent Topsectors. Our data indicate several effects taking place at the broader NUTS 3 geographical level, in this respect.

A plausible explanation is that because other Topsector industries are by definition active in different sectors, such firms are not compelled to locate in a 'Life Science and Health' cluster to internalise the unique, cluster-specific, related knowledge, as proposed by e.g. Marshall (1920). Rather, such firms will prefer to engage in formal collaborative networks to attain relevant knowledge, when needed. Spatial proximity thus becomes less important, as these collaborations can easily take place at the extra-regional geographical level.

7 Conclusion

This research has attempted to investigate the potential beneficial effects of regional specialisation in Topsector 'Life Science and Health' on economic growth, by also considering the theorised importance of related industries collocating at such cluster locations. As such, in this research we move beyond the traditional dyad in the long-standing debate in economic geography concerned with the importance of either specialisation or diversification to economic growth (Boschma, 2009).

The rationale for this research has been to provide improved empirical justification for the current targeted state funding policies, i.e. 'Topsectoren Beleid' (Ministerie van Economische Zaken, 2011; Raspe et al., 2012), by also broadening the sectoral definition of the Topsector 'Life Science and Health' to include related industries sharing cognitive proximity. Earlier examinations of the effectiveness of the current 'Topsectoren Beleid' policies have – until very recently – not considered related industries (Centraal Bureau voor de Statistiek, 2012).

We have tried to identify related diversity by means of branch-wise analysis of the Dutch standard hierarchical industry classification system. However, this method is in no way without difficulties (Neffke and Henning, 2010). Primarily, the way in which we identified related industries in this research, may in some cases seem rather arbitrary. This may account for the limited empirical proof of the beneficial effects of regional specialisation in related industries.

It is only when we strictly abide by the classification method proposed by Boschma and Iammarino (2009), that we find compelling evidence for the direct beneficial effects of related industries collocating at 'Life Science and Health' clusters.

With the exclusion of spinoffs dynamics, we have found indirect evidence of the importance of the mechanisms of both labour mobility and collaborative networking for the regional dissemination of related knowledge, as proposed by Boschma (2009).

Quantitative analysis along this line of reasoning could perhaps be supplemented with detailed studies of the regional economic landscape to identify important related industries more concisely (Boschma and Iammarino, 2009).

This is particularly important when the 'Topsectoren Beleid' may prove to be in need of revising towards being inclusive of related diversity, provided that empirics will eventually surmount to a convincing body of proof for the economic relevance of related industries.

Specific cases can be considered to create synergies between related industries through system integration (Von Tunzelmann, 2003), which is now starting to take shape, e.g. the province of Noord-Brabant has granted additional funding for improving the regional network between several related, specialised regions (Ministerie van Economische Zaken, 2011).

As such, the current sectoral policies plan may eventually have to develop back into the direction of cluster-based targeted policies (Glasmeier, 2000).

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Appendix A Related Diversity in SBI-2008

Table A.1 SBI-2008 overview 'Life Science and Health' (in Dutch)

21 Vervaardiging van farmaceutische grondstoffen en producten	
21.1	Vervaardiging van farmaceutische grondstoffen
21.10	Vervaardiging van farmaceutische grondstoffen
21.2	Vervaardiging van farmaceutische producten (geen grondstoffen)
21.20	Vervaardiging van farmaceutische producten (geen grondstoffen)
26 Vervaardiging van computers en van elektronische en optische apparatuur	
26.1	Vervaardiging van elektronische componenten en printplaten
26.11	Vervaardiging van elektronische componenten
26.12	Vervaardiging van elektronische printplaten
26.2	Vervaardiging van computers en randapparatuur
26.20	Vervaardiging van computers en randapparatuur
26.3	Vervaardiging van communicatieapparatuur
26.30	Vervaardiging van communicatieapparatuur
26.4	Vervaardiging van consumentenelektronica
26.40	Vervaardiging van consumentenelektronica
26.5	Vervaardiging van meet-, regel-, navigatie- en controleapparatuur en van uurwerken
26.51	Vervaardiging van meet-, regel-, navigatie- en controleapparatuur
26.52	Vervaardiging van uurwerken
26.6	Vervaardiging van bestralingsapparatuur en van elektromedische en Elektrotherapeutische apparatuur
26.60	Vervaardiging van bestralingsapparatuur en van elektromedische en Elektrotherapeutische apparatuur
26.7	Vervaardiging van optische instrumenten en apparatuur
26.70	Vervaardiging van optische instrumenten en apparatuur
26.8	Vervaardiging van informatiedragers
26.80	Vervaardiging van informatiedragers
32 Vervaardiging van overige goederen	
32.1	Slaan van munten; bewerken van edelstenen en vervaardiging van sieraden
32.11	Slaan van munten en medailles
32.12	Bewerken van edelstenen en vervaardiging van sieraden e.d. (geen imitatie)
32.13	Vervaardiging van imitatiesieraden
32.2	Vervaardiging van muziekinstrumenten
32.20	Vervaardiging van muziekinstrumenten
32.3	Vervaardiging van sportartikelen
32.30	Vervaardiging van sportartikelen
32.4	Vervaardiging van speelgoed en spellen
32.40	Vervaardiging van speelgoed en spellen
32.5	Vervaardiging van medische instrumenten en hulpmiddelen
32.50	Vervaardiging van medische instrumenten en hulpmiddelen
32.50.1	Tandtechnische bedrijven
32.50.2	Vervaardiging van medische instrumenten en hulpmiddelen (geen tandtechniek)
32.9	Vervaardiging van overige goederen
32.91	Vervaardiging van borstelwaren
32.99	Sociale werkvoorziening en vervaardiging van overige goederen n.e.g.

32.99.1	Sociale werkvoorziening
32.99.9	Vervaardiging van overige goederen n.e.g.
72 Speur- en ontwikkelingswerk	
72.1	Natuurwetenschappelijk speur- en ontwikkelingswerk
72.11	Biotechnologisch speur- en ontwikkelingswerk
72.11.1	Biotechnologisch speur- en ontwikkelingswerk op het gebied van agrarische producten en processen
72.11.2	Biotechnologisch speur- en ontwikkelingswerk op het gebied van medische producten en farmaceutische processen en van voeding
72.11.3	Biotechnologisch speur- en ontwikkelingswerk voor overige toepassingen
72.19	Natuurwetenschappelijk speur- en ontwikkelingswerk (niet Biotechnologisch)
72.19.1	Speur- en ontwikkelingswerk op het gebied van landbouw en visserij (niet Biotechnologisch)
72.19.2	Technisch speur- en ontwikkelingswerk
72.19.3	Speur- en ontwikkelingswerk op het gebied van gezondheid en voeding (niet Biotechnologisch)
72.19.9	Overig natuurwetenschappelijk speur- en ontwikkelingswerk (niet Biotechnologisch)
72.2	Speur- en ontwikkelingswerk op het gebied van de maatschappij- en geesteswetenschappen
72.20	Speur- en ontwikkelingswerk op het gebied van de maatschappij- en geesteswetenschappen

(Source: Centraal Bureau voor de Statistiek, 2013) 'Life Science and Health' sectors denoted in bold

Appendix B Alternative Approach to Related Diversity

This research has employed an interaction variable LQ.INTRCT.JOB.LSH.RD.6 to investigate the potential reciprocal benefits of having related diversified industries at 'Life Science and Health' clusters for boosting economic growth there.

Similar to the work of Boschma and Iammarino (2009), an alternative definition for this interaction effect has also been tested. However, this did not yield any additional insights and was thus omitted from the research. Yet, it makes sense to include these results here to demonstrate that the way interaction between regional specialisation and related industries is measured makes quite the difference in terms of interpreting the results.

This alternative definition for measuring the interaction effect is used to indicate the level of entropy between the 'Life Science and Health' sectors and related diversified industries, be it defined 'Full,' 'Research,' or 'Topsector' as described in section 4.2.2 (variable ENTRPY.JOB.LSH.RD.6).

Boschma and Iammarino (2009) suggest that regional entropy *S* between two sets of industries in any region *r*, can be defined as employment *E* in 'Life Science and Health' divided by employment in related diversified industries, multiplied by the binary logarithm of one over the ratio of employment in 'Life Science and Health' sectors and employment in related diversified industries, or:

$$S_r = \frac{E_{LSHr}}{E_{RDr}} \times \mathrm{LOG}_2\left(\frac{1}{E_{LSHr} / E_{RDr}}\right).$$

S_r denotes the entropy measure for region *r*, i.e. the entropic interaction between employment in 'Life Science and Health' E_{LSHr} and related diversity E_{RDr}.

Lower values for S_r indicates a higher potentials for relevant knowledge-sharing as both sets of industries are occurring more evenly in that particular municipality. A positive value indicates an over-representation of related diversified industries. Values of zero differ from missing values in that the former allows potentially for 'Life Science and Health' firms to start-up in the future stemming from related diversified firms in the vicinity, whereas a missing value indicates a complete lack of related knowledge for current 'Life Science and Health' firms to theoretically benefit from.
Table B.3 adds to table 4.1 in section 4.4 to include the simple statistics of the regression sample for the entropy variables calculated by using the three alternative definitions of related diversity used in this research (described in section 4.2.2). Notably, due to the way it is calculated the entropy variable induces several missing values compared to the interaction variable used in this result.

Table B.1 Simple Statistics of the Regression Sample

Variable	N	Min.	Max.	Mean	Std. Dev.
ENTRPY.LSH.RDFULL.6	405	-96,114	0,531	-1,065	8,465
ENTRPY.NUT.RDFULL.6	415	0	0,530	-433,458	2039,269
ENTRPY.RDRSCH.6	319	-5585,931	0,530	-58,368	393,213
ENTRPY.NUT.RDRSCH.6	415	0	0,530	-445,515	2036,999
ENTRPY.RDTOPS.6	415	-2,175	0,528	0,044	0,161
ENTRPY.NUT.RDTOPS.6	415	0	0,500	-433,539	2039,251

Tables B.2 and B.3 below show the regression estimates for both types of models used in this research (see section 4.3 for detailed description of the regression equations).

Strikingly, in model 1 the variable ENTRPY.JOB.LSH.RD.6 for each definition of related diversity is shown to be highly significant at the highest confidence level, whereas no significance is indicated for said measure in the second model.

Also, a strong, negative entropy coefficient measure is considered the most beneficial for firms to benefit from cognitive proximity, however, table B.4 does not support the direction of the coefficients for this assumption consistently.

Table B.2 Model 1 with Entropy Measure for Related Diversity

Variable	Full	Research	Topsector
Constant	-544,547 (476,369)	-408,519 (397,105)	-535,523 (450,716)
log(JOB.LSH.6)	6,459 (5,327)	8,632** (4,639)	-17,782*** (6,765)
LQ.JOB.LSH.6	-32,497*** (3,288)	2,238 (3,203)	-18,069*** (3,367)
LQ.JOB.NUT.LSH.6	-6,901 (6,277)	4,931 (7,550)	19,860 (12,558)
LQ.JOB.RDFULL.6	,772 (8,575)		
LQ.JOB.NUT.RDFULL.6	12,423 (18,306)		
LQ.ENTRPY.JOB. RDFULL.6	-5,943*** (,909)		
LQ.ENTRPY.JOB.NUT. RDFULL.6	-18,171 (25,056)		
LQ.JOB.RDRSCH.6		-,987 (1,881)	
LQ.JOB.NUT.RDRSCH.6		-4,189 (7,480)	
LQ.ENTRPY.JOB. RDRSCH.6		,274*** (,020)	
LQ.ENTRPY.JOB.NUT. RDRSCH.6		,372 (,328)	
LQ.JOB.RDTOPS.6			17,222 (19,391)
LQ.JOB.NUT.RDTOPS.6			-36,088 (32,286)
LQ.ENTRPY.JOB.			429,127***

RDTOPS.6			(61,813)
LQ.ENTRPY.JOB.NUT. RDTOPS.6			-386,376** (170,759)
POP.DENS.6	,004 (,010)	,002 (,008)	,008 (,010)
LAB.FORCE.REL.6	377,794 (446,394)	520,494 (375,695)	499,054 (430,542)
EDU.REL.6	3,499*** (1,752)	,500 (1,519)	4,076** (1,706)
AVG.FIRM.LSH.6	,296 (,065)	,045 (,056)	,567*** (,076)
log(HOUSE.VALUE.6)	42,812 (54,253)	10,460 (44,369)	36,270 (52,638)
DUMMY.UNI	47,486* (27,999)	1,863 (22,747)	52,272* (27,473)
R-squared	,419	,669	,444
Adj. R-squared	,378	,643	,405
F	10,167***	24,921***	11,263***

Dependent Variable: DELTA.JOB.LSH. N = 196. Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Table B.3 Model 2 with Entropy Measure for Related Diversity

Variable	Full	Research	Topsector
Constant	-3,709 (4,022)	-4,915 (4,159)	-5,771 (3,878)
log(JOB.LSH.6)	,838*** (,045)	,820*** (,049)	,822*** (,058)
LQ.JOB.LSH.6	,000 (,028)	,017 (,034)	,026 (,029)
LQ.JOB.NUT.LSH.6	-,020 (,053)	,010 (,079)	,068 (,108)
LQ.JOB.RDFULL.6	-,045 (,072)		
LQ.JOB.NUT.RDFULL.6	-,095 (,155)		
LQ.ENTRPY.JOB. RDFULL.6	-,006 (,008)		
LQ.ENTRPY.JOB.NUT. RDFULL.6	,080 (,212)		
LQ.JOB.RDRSCH.6		-,013 (,020)	
LQ.JOB.NUT.RDRSCH.6		,006 (,078)	
LQ.ENTRPY.JOB. RDRSCH.6		4,375E-005 (,000)	
LQ.ENTRPY.JOB.NUT. RDRSCH.6		,000 (,003)	
LQ.JOB.RDTOPS.6			-,236 (,167)
LQ.JOB.NUT.RDTOPS.6			,003 (,278)

LQ.ENTRPY.JOB. RDTOPS.6			,184 (,532)
LQ.ENTRPY.JOB.NUT. RDTOPS.6			-1,516 (1,469)
POP.DENS.6	4,600E-005 (,000)	5,577E-005 (,000)	4,125E-005 (,000)
LAB.FORCE.REL.6	7,906** (3,769)	9,129** (3,935)	8,660** (3,705)
EDU.REL.6	,015 (,015)	,019 (,016)	,016 (,015)
AVG.FIRM.LSH.6	,000 (,001)	,000 (,001)	,000 (,001)
log(HOUSE.VALUE.6)	-,234 (,458)	-,184 (,465)	,113 (,453)
DUMMY.UNI	,129 (,236)	,049 (,238)	,147 (,236)
R-squared	,816	,820	,817
Adj. R-squared	,803	,806	,804
F	62,286***	56,145***	62,772***

Dependent Variable: log(JOB.LSH.11). N = 196. Standard errors are reported in parentheses.
*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively

Appendix C Correlations

Table C.1 Correlations

	Variable	1	2	3	4	5	6	7
1	DELTA.JOB.LSH							
2	log(JOB.LSH.6)	-0,07						
3	log(JOB.LSH.11)	0,01	**,910**					
4	LQ.JOB.LSH.6	**-,392**	**,536**	**,489**				
5	LQ.JOB.NUT.LSH.6	-0	**,253**	**,220**	**,123**			
6	LQ.JOB.RDFULL.6	-0,04	**,178**	**,163**	0,03	0,05		
7	LQ.JOB.NUT.RDFULL.6	0	0,03	0,01	0,02	0,01	**,166**	
8	LQ.JOB.RDRSCH.6	0,05	**,115**	**,132**	0,03	0,06	**,412**	0,01
9	LQ.JOB.NUT.RDRSCH.6	0,05	**,125**	**,129**	0,07	0,04	0,04	**,282**
10	LQ.JOB.RDTOPS.6	0	**-,301**	**-,309**	-0,09	**-,128**	-0,06	0,09
11	LQ.JOB.NUT.RDTOPS.6	-0,03	0,08	0,09	0,02	-0,02	**,174**	**,213**
12	INTRCT.LQ.RDFULL.6	**-,624**	**,476**	**,416**	**,766**	**,128**	**,218**	0,01
13	INTRCT.LQ.NUT. RDFULL.6	0,02	**,251**	**,219**	**,131**	**,919**	0,05	**,181**
14	INTRCT.LQ.RDRSCH.6	**,103**	**,251**	**,246**	**,362**	0,03	**,192**	-0,04
15	INTRCT.LQ.NUT. RDRSCH.6	0,08	**,194**	**,204**	**,096**	**,420**	-0,01	**,130**
16	INTRCT.LQ.RDTOPS.6	**-,278**	**,498**	**,454**	**,931**	**,131**	0,02	0,01
17	ENTRPY.RDFULL.6	-0,06	**-,316**	**-,298**	**-,586**	**-,145**	0,07	-0,03
18	ENTRPY.NUT.RDFULL.6	0	**,136**	**,116**	0,05	**,103**	0,01	0,1
19	ENTRPY.RDRSCH.6	**,779**	**-,353**	**-,313**	**-,660**	-0,06	-0,05	0,01
20	ENTRPY.NUT.RDRSCH.6	0	**,134**	**,114**	0,04	0,1	0,01	0,1
21	ENTRPY.RDTOPS.6	**,349**	**,361**	**,318**	**-,300**	**,122**	0,08	-0,01
22	ENTRPY.NUT.RDTOPS.6	0	**,136**	**,116**	0,05	**,103**	0,01	0,1
23	POP.DENS.6	0,09	**,390**	**,401**	0,07	**,111**	0,09	**-,145**
24	LAB.FORCE.REL.6	0,01	**,130**	**,128**	0,05	0,05	-0,02	-0,03
25	EDU.REL.6	0,1	**,340**	**,363**	**,158**	**,212**	0,02	**-,175**
26	AVG.FIRM.LSH.6	**-,169**	**,390**	**,363**	**,783**	0,05	0	0,03
27	log(HOUSE.VALUE)	-0,01	-0,08	-0,1	0,05	**,273**	**-,313**	**-,186**
28	DUMMY.UNI	0,09	**,179**	**,183**	0,07	0,02	-0,01	0,04
		8	9	10	11	12	13	14
9	LQ.JOB.NUT.RDRSCH.6	**,165**						
10	LQ.JOB.RDTOPS.6	**,182**	0,03					
11	LQ.JOB.NUT.RDTOPS.6	**,134**	**,247**	**,161**				
12	INTRCT.LQ.RDFULL.6	**,168**	0,05	-0,09	0,04			
13	INTRCT.LQ.NUT. RDFULL.6	0,04	**,105**	**-,098**	0	**,116**		
14	INTRCT.LQ.RDRSCH.6	**,483**	0,02	0,03	0,01	**,446**	0,02	
15	INTRCT.LQ.NUT. RDRSCH.6	0,01	**,464**	**-,137**	0,05	0,05	**,515**	0,01
16	INTRCT.LQ.RDTOPS.6	0,06	0,02	-0,02	0,04	**,642**	**,135**	**,432**
17	ENTRPY.RDFULL.6	0,01	-0,05	0	-0,02	**-,154**	**-,173**	**-,130**
18	ENTRPY.NUT.RDFULL.6	0,03	**,097**	-0,08	-0,07	0,04	**,100**	0,02
19	ENTRPY.RDRSCH.6	0,03	0,03	0,09	0,03	**-,744**	-0,05	-0,01

20	ENTRPY.NUT.RDRSCH.6	0,03	**,100**	-0,08	-0,07	0,04	0,09	0,02
21	ENTRPY.RDTOPS.6	0,05	0	**-,127**	-0,03	**-,273**	**,124**	0,06
22	ENTRPY.NUT.RDTOPS.6	0,03	**,097**	-0,08	-0,07	0,04	**,100**	0,02
23	POP.DENS.6	0,06	**,182**	**-,460**	**-,129**	0,1	0,09	0,06
24	LAB.FORCE.REL.6	0,03	0,03	**-,149**	-0,03	0,05	0,04	0,03
25	EDU.REL.6	**,214**	**,138**	**-,145**	**-,115**	**,162**	**,133**	**,285**
26	AVG.FIRM.LSH.6	0	0,11	-0,07	0,07	**,539**	0,06	**,147**
27	log(HOUSE.VALUE)	0,03	**,121**	0,08	**-,233**	0	**,215**	0,04
28	DUMMY.UNI	0,06	**,172**	**-,146**	**-,204**	0,04	0,05	0,08
		15	16	17	18	19	20	21
16	INTRCT.LQ.RDTOPS.6	0,05						
17	ENTRPY.RDFULL.6	**-,177**	**-,709**					
18	ENTRPY.NUT. RDFULL.6	0,07	0,04	-0,03				
19	ENTRPY.RDRSCH.6	0	**-,546**	**,231**	-0,03			
20	ENTRPY.NUT.RDRSCH.6	0,07	0,04	-0,02	**1,000**	-0,02		
21	ENTRPY.RDTOPS.6	0,09	**-,124**	**-,110**	0,06	**,264**	0,06	
22	ENTRPY.NUT.RDTOPS.6	0,07	0,04	-0,03	**1,000**	-0,03	**1,000**	0,06
23	POP.DENS.6	**,232**	0,01	0,01	**,129**	-0,02	**,129**	**,212**
24	LAB.FORCE.REL.6	0,04	0,04	-0,02	0,08	-0,04	0,08	0,06
25	EDU.REL.6	**,258**	**,138**	-0,06	0,09	0	0,09	**,121**
26	AVG.FIRM.6	0	**,659**	**-,454**	0,04	**-,373**	**-,151**	**-,561**
27	log(HOUSE.VALUE)	**,171**	0,06	-0,04	**,217**	0,01	**,214**	-0,06
28	DUMMY.UNI	**,197**	0,05	-0,04	0,07	0,04	0,08	**,120**
		22	23	24	25	26	27	
23	POP.DENS.6	**,129**						
24	LAB.FORCE.REL.6	0,08	**,212**					
25	EDU.REL.6	0,09	**,339**	0,07				
26	AVG.FIRM.6	**,171**	0,02	0,04	0,04			
27	log(HOUSE.VALUE)	**,218**	**-,180**	**-,358**	**,274**	0,05		
28	DUMMY.UNI	0,07	**,276**	0,09	**,264**	-0,02	0,02	

Coefficients reported in bold are significant at the 5% level (2-tailed)