The Development of Technology Cluster Innovation Performance: Health and Sustainable Energy

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The Development of Technology Cluster Innovation Performance: Health and Sustainable Energy

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Chapter 1

Introduction

1.1 Global Sustainability Challenges and Innovation Performance

Decades of rapid economic and technological progress have raised living standards and life expectancy in many parts of the world. Yet this progress has also created new global challenges such as climate change (Intergovernmental Panel on Climate Change 2015, 2018) and ageing populations (European Commission 2010; World Health Organization 2019). Technological innovation is expected to play an important role in addressing these sustainability challenges (European Commission 2013, 2014b, 2019; United Nations 2015).

The urgency of the sustainability challenges is highlighted in official reports by the World Health Organization and the Intergovernmental Panel on Climate Change. Concerning the global impact of ageing populations, the World Health Organization notes that:

> Rapid population ageing in low- and middle-income countries is an emergent, unprecedented dynamic with unique implications and opportunities for these societies, as well as for other more aged societies … while the financial impact [of ageing] is not predicted to be catastrophic, it still represents an important, complex concern for decision-makers. (World Health Organization 2004, 2)

Ageing populations increase demand for medical care and raise concern about its affordability. If increasing demand and costs are not addressed then ageing populations may threaten the sustainability of national healthcare systems (European Commission 2018; World Health Organization 2019). With regard to climate change, the Intergovernmental Panel on Climate Change (IPCC) has warned that:

> Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, and sea level has risen. … Human influence on the climate system is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history. Recent climate changes have had widespread impacts on human and natural systems. (Intergovernmental Panel on Climate Change 2015, 2)

To address the challenge of an ageing population, the World Health Organization draws attention to the importance of "social and technological innovations in potentially cost-effective, scalable solutions" (World Health Organization 2004, 7) to ensure that healthcare remains accessible and affordable. Concerning climate change, the International Energy Agency and the United Nations Environment Program also emphasize the role of technological innovation in the sustainable energy sector to help address the challenges related to climate change (International Energy Agency 2016; REN21 2017). Innovation, climate change, public health and the need for sustainable industrialization and economic growth are also mentioned in the Sustainable Development Goals, which were adopted by the United Nations General Assembly in 2015, signaling their relevance in international politics (United Nations 2017). The social and economic importance of health and sustainable energy innovations suggests that they occur within a broader context of socio-technological transitions that involve not only technological innovations but also changes in social behavior, regulation and economic activity (Geels et al. 2011; Geels 2012; Ohta 2019).

Along with socio-technological transitions, changes in the global spatial distribution of innovation activity are also underway. Most prominent among these is the rapid and sustained increase in innovation performance in parts of Asia (Hobday 1995; Hu and Mathews 2005). Concisely defined, innovation performance is the ability to generate new knowledge and apply it in an economically useful way (Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005). Innovation generates great economic value, both for the innovators and for society in general (Nordhaus 2004; Tidd, Bessant, and Pavitt 2005) and as a result the innovation performance of firms and knowledge creating institutions is one of the main determinants of long-term economic success and a nation's global standing (Tidd, Bessant, and Pavitt 2005; Dicken 2007; European Commission 2010, 2013). The increasing innovation performance in Asia and the continuing high innovation performance of the United States have understandably raised concerns among European policy makers, who fear that lagging innovation performance will erode the long-term global economic competitiveness of Europe and its global economic, social and political influence (European Commission 2010, 2013). In assessing the European Union's science and technology development, the European Commission (2013) notes:

> Science and technology development in Asia and the United States are more focused on transformative and pervasive technologies and more oriented towards emerging global markets. The United States is strengthening its profile as a world leading center for science and technology in health, biotechnologies, nanotech and ICT. China is the world's biggest producer of scientific publications in the fields of energy and ICT, while Japan has the highest rate of technology development in energy and in environmental technologies. In comparison, the EU is less focused on strategic areas and tends to scatter its efforts on a wider range of scientific fields and technologies, with the risk of dominating none. (European Commission 2013, 8)

As an indication of the seriousness of these concerns, the European Union has launched the 80 billion euro Horizon 2020 program to raise the innovation performance of its member countries (European Commission 2010). Meanwhile the Netherlands has announced a 20 billion euro National Growth Fund which aims to enhance Dutch economic and innovation performance (General Affairs 2020). The global geopolitical importance of innovation performance is also shown by the current trade disputes between China and the United States. The dispute over the export of 5G telecommunication network equipment by China's Huawei concerns American objections to the acquisition of high technology by Chinese firms and American attempts to block the export of Chinese high technology products (Fan 2019a).

The global importance of health and sustainable energy technology creates an urgent need for a global analysis of innovation performance of the two sustainability technology sectors. The current literature suggests that such a global analysis should focus on technology clusters because it is increasingly clear that many of the factors influencing innovation performance act at the cluster scale (Cooke 2007; Crescenzi and Rodríguez-Pose 2011; Crescenzi et al. 2019). The analysis should also include global knowledge networks, which play an important role as enablers or enhancers of cluster innovation performance (Bathelt, Malmberg, and Maskell 2004; Ter Wal and Boschma 2011; Crescenzi et al. 2019). In addition the literature notes important differences between technological sectors from an evolutionary perspective, namely their phase of development (Ter Wal and Boschma 2011; Alkemade et al. 2015; Frenken, Cefis, and Stam 2015), and from the perspective of their knowledge base (Asheim and Coenen 2005; Stankiewicz 2002; Davids and Frenken 2018). These sectoral differences appear to influence innovation performance on a global scale. Viewed from these theoretical perspectives, the research in this dissertation addresses three main knowledge gaps:

I. The changing global spatial distribution, agglomeration patterns and global knowledge networks of sustainability technology clusters,

II. The relationship between the innovation performance of sustainability technology clusters and their agglomeration, knowledge network, national innovation system and path dependence characteristics,

III. The influence of socio-technological transitions, sectoral knowledge base and development phase on sustainability technology clusters, including the innovation performance of these clusters.

The aforementioned knowledge gaps arise because of a lack of research and innovation-related data about the sustainability technology sectors that is global in scope, yet at the spatial scale of technology clusters. This hinders statistical analysis of the relationship between innovation performance and other cluster characteristics. The lack of data also limits the analysis of how socio-technological transitions, the sectoral knowledge base and the sectoral development phase influence the innovation performance of sustainability technology clusters.

The dissertation's research aims and objectives follow from these knowledge gaps (section 1.2), which in turn lead to the research questions (section 1.3). The research questions are followed by a discussion of the research relevance (section 1.4). Chapter 1 concludes with an outline of the research approach and dissertation structure (section 1.5).

1.2 Research Aims and Objectives

The aim of this dissertation is to understand how health technology and sustainable energy technology clusters have developed spatially and over time. The research explores the locations of these technology clusters and the cluster characteristics associated with high innovation performance. These insights, which are further discussed below, can enhance current empirical and theoretical perspectives on cluster innovation performance and provide information for policy makers seeking to raise the innovation performance of sustainability technology clusters.

While there is an extensive literature on evolutionary economic geography (Trippl et al. 2015), innovation systems (Pino and Ortega 2018; Suominen, Seppänen, and Dedehayir 2019) and global innovation diffusion (Zanello et al. 2016), the extent to which these theoretical perspectives apply to all sectors is often unclear. There are significant differences between sectors in terms of how knowledge is created and transmitted (Pavitt 1984; Malerba and Orsenigo 1997; Battistella, De Toni, and Pillon 2016; Fabiano, Marcellusi, and Favato 2020), and in the evolutionary path or development phase of sectors (Ter Wal and Boschma 2011). Innovation activity is known to vary depending on the regional and national context, such as the local presence of research-intensive universities or research funding (Zanello et al. 2016; Szczygielski et al. 2017; Miao et al. 2018; Pino and Ortega 2018). Accordingly, although sectoral innovation processes are global in their scale, involving researchers and organizations from around the world (Dicken 2007; Binz and Truffer 2017), local and sector-specific factors can significantly influence cluster innovation performance (Gertler and Wolfe 2006; Binz and Truffer 2017).

Complementing these general theoretical perspectives are a wealth of sector case studies with different spatial scales, scopes and objectives. While such sector case studies are insightful, they usually lack a global perspective and their value in cross-sector comparisons is limited due to differences in research approach, methodology and the countries or technology clusters being studied. Comparative global studies of multiple sectors are relatively rare (Castellani, Jimenez, and Zanfei 2013; Alkemade et al. 2015) and appear non-existent for sustainability technology sectors. This knowledge gap and the limitations of sector case studies can be illustrated by the photovoltaics sector, one of the most extensively studied sustainable energy sectors in recent years. Academic studies of the photovoltaics sector have focused on specific countries in the context of industrial policy, national and international technology transfer and competition (De La Tour, Glachant, and Ménière 2011; Grau, Huo, and Neuhoff 2012; Vidican et al. 2012; Klitkou and Godoe 2013; Lo, Wang, and Huang 2013; Wu 2014; Zheng and Kammen 2014; Kim and Kim 2015). In some of these studies a comparisons between a small number of countries is made. These comparisons include China, Germany, South Korea, Norway, Taiwan and the United Arab Emirates and a group of European countries (Monforti, Gaetani, and Vignati 2016). There are also studies of specific technology clusters (or cities/regions) within a country (Boeckle et al. 2010; Klitkou and Coenen 2013; West 2014; Dewald and Fromhold-Eisebith 2015; Luo, Lovely, and Popp 2017; Nielsen 2017). However, only a few global studies explore the worldwide growth and spatial distribution of photovoltaics innovation at the country-level (Breyer et al. 2013) and the cluster-level (Leydesdorff et al. 2014).

The lack of specificity of current theories about innovation performance, combined with a lack of results from sectoral case studies that can be generalized to other sustainability technology sectors, leads to the formulation of the four research objectives of this dissertation. The first objective concerns the need to develop a methodology to identify and characterize sustainability technology clusters on a global scale. The second and third research objectives seek to develop a deeper understanding of the global spatial distribution of sustainability technology clusters and global inter-cluster knowledge networks based on the new methodology. The fourth research objective is concerned primarily with the innovation performance of sustainability technology clusters. The objectives are presented first, followed by the reasons for their inclusion in this study.

Objective 1: To develop a methodology for identifying and characterizing sectoral technology clusters on a global scale.

Currently, there is no global data set of innovation indicators describing *sectoral* technology clusters. While there are global innovation performance indexes at the national level (Schwab and Sala-i-Martin 2015; Dutta and Lanvin 2016) and sub-national studies describing aggregate innovation at the regional or city level (Bergquist, Fink, and Raffo 2017; Hollanders, Es-Sadki, and Merkelbach 2019), these studies lack sectoral data. Scientometric data such as patents and scientific publications have been used to identify life sciences, photovoltaics and semiconductor clusters on a global scale (Duranton and Overman 2005; Leydesdorff et al. 2014; Catini et al. 2015; Alcácer and Zhao 2016). Unfortunately these studies have not gone beyond a descriptive analysis of cluster locations, size or global knowledge networks (Leydesdorff et al. 2014) and they have not addressed measurement issues such as the home-bias effect (Bacchiocchi and Montobbio 2010). Hence there is no clear global overview on sustainability technology clusters. In this study sustainability technology clusters are defined as spatial concentrations of sustainable energy technology-related R&D.

The cluster identification methodology developed in this dissertation can be applied to any sector that produces sufficient patents, including the sustainability technology sectors. The methodology addresses known measurement biases (Bacchiocchi and Montobbio 2010; Laurens et al. 2015) and adopts spatial analysis methods from fields used in statistics (Rosenblatt 1956; Parzen 1962) and public health (Han et al. 2016; Ma et al. 2016). After completing the cluster identification process innovation indicators are extracted from the identified cluster data. These indicators are then used for descriptive and explanatory analysis of sustainability technology clusters in this study.

Objective 2: To analyze the changing global spatial distribution of sustainability technology clusters.

The aforementioned lack of data about the spatial distribution and innovation performance of sustainability technology clusters means that relatively little is known about the location, size or country-distribution of health technology and sustainable energy technology clusters. Yet a global study at the cluster scale has important benefits. First, it allows global shifts in innovation activity to be observed at the very important cluster scale (Porter 2000; Dicken 2007; Miao et al. 2018). Second, the observation of clusters over time offers an opportunity to explore the path-dependence of innovation activity, which appears to manifest itself strongly at the regional level but is not fully understood, especially in relation to sustainability technology sectors and socio-technological transitions (Boschma and Frenken 2006; Crescenzi and Rodríguez-Pose 2011). Third, a global cluster study allows comparison to be made between different types of sectors and sectoral clusters (Iammarino and McCann 2006). Agglomeration and the inter-cluster knowledge network characteristics are of particular interest because of their perceived importance to cluster innovation performance and are addressed under objective 3 (Porter 2000; Bathelt, Malmberg, and Maskell 2004; Boschma 2005; Gertler and Levitte 2005; Capello 2009).

Objective 3: To analyze agglomeration and knowledge network characteristics of sustainability technology clusters.

Agglomeration characteristics, such as economies of scale or adjacency to nearby clusters, have been shown to vary across sectors and clusters based on variations in institutional structures (Breschi and Malerba 1997; Iammarino and McCann 2006), the sectoral knowledge base (Stankiewicz 2002; Asheim and Coenen 2005), and the development phase of a sector (Martin and Simmie 2008; Martin and Sunley 2011; Ter Wal and Boschma 2011). Differences in agglomeration can be reflective of different kinds of innovation processes taking place in a particular sector (Tidd 2001; Binz and

Truffer 2017). Earlier empirical work by Castellani, Jimenez, and Zanfei (2013) and Alkemade et al. (2015) has shown that research collaboration knowledge networks also vary by industry sector, with the healthcare and pharmaceuticals sector in particular showing a high frequency of international research collaborations.

A greater understanding of sectoral differences in spatial distribution, agglomeration, and knowledge networks provides context for a statistical analysis of technology cluster innovation performance. Analyzing agglomeration characteristics and knowledge network characteristics leads to Objective 4, which concerns an attempt to attribute variations in cluster innovation performance to differences in the spatial distribution, agglomeration, and knowledge network characteristics of technology clusters.

Objective 4: To analyze the cluster characteristics associated with the innovation performance of sustainability technology clusters.

The relationship between various cluster or regional characteristics and innovation output has been successfully explored in a number of previous studies. These studies involved the development of knowledge production functions incorporating agglomeration, knowledge networks and path dependence (Ó hUallacháin and Leslie 2007; Ponds, Oort, and Frenken 2009; Charlot, Crescenzi, and Musolesi 2014; Crescenzi and Jaax 2017). An adaptation of such a knowledge production function, a cluster innovation performance model, is implemented in this study, in order to identify the cluster characteristics associated with the innovation performance of sustainability technology clusters.

A greater understanding of the development and spatial distribution of sustainability technology clusters is also very relevant from a policy perspective, which leads to a fifth and final research objective for this study.

Objective 5: To explore the policy relevance of the cluster identification methodology and the research results.

Innovation policies focused on sustainability technologies are high on national and international policy agendas, and will likely remain there as challenges related to climate change, ageing and public health increase (World Health Organization 2004; Intergovernmental Panel on Climate Change 2015). However the implementation of these policy goals also takes place at the level of cities and spatial clusters (Bulkeley et al. 2016; Evans, Karvonen, and Raven 2016; Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Nejabat 2021). Therefore the identification of technology clusters, and an enhanced understanding of the factors associated with cluster innovation performance, provide important information that can be used to evaluate and improve cluster-level innovation policies. These insights are also relevant from the perspective of national and European economic competitiveness, as clusters are widely seen as a spatial level that can strongly influence innovation performance (European Commission 2013). The policy relevance of the research is briefly discussed in section 7.5 of chapter 7 in order to give directions for future in-depth research.

1.3 Research Questions

The main research question addressed in this dissertation is:

What are the dynamic spatial distribution and innovation performance patterns of sustainability technology clusters and how are they influenced by cluster characteristics, such as agglomeration *and knowledge networks, and sectoral differences?*

Eight research sub-questions address the different aspects of sustainability technology clusters, their spatial distribution and the factors associated with cluster innovation performance. Research sub-question 1 and 2 address the global spatial distribution, agglomeration and knowledge network characteristics of sustainability technology clusters. Research sub-questions 3-6 cover the (mutual) causal relationship between cluster innovation performance and agglomeration, national innovation system, knowledge networks and path dependence characteristics of the cluster. Research sub-question 7 and 8 direct attention to the sectoral differences between health technology and sustainable energy technology clusters and other high technology sectors

The research sub-questions are based on two different theoretical perspectives of technology clusters: a spatial perspective and an institutional or systems perspective. From a spatial perspective, technology clusters are viewed as spatial concentrations of innovation activity from a particular sector. Although technology clusters are found in globally distributed locations, they are part of interconnected global knowledge and business networks (Feldman and Florida 1994; Audretsch and Feldman 1996b; Breschi and Malerba 1997; Castells 2010). Viewed from an institutional or systems perspective, a technology cluster is part of a global sectoral innovation system, which is influenced by global networks of suppliers, customers, and competitors (Porter 2000; Binz and Truffer 2017). The globalization of sectoral innovation systems is partly driven by organizations seeking to acquire the best research and ideas (and the people behind them) at the most competitive price, regardless of their location (Audretsch, Lehmann, and Wright 2014; Locke and Wellhausen 2014). Globalization is also driven by increasing technological complexity and global competitive pressures, coupled with the falling cost and rising quality of transportation and communications technologies, which facilitate research and business activities over long distances (Bruche 2009; Audretsch, Lehmann, and Wright 2014; Locke and Wellhausen 2014; Alkemade et al. 2015).

In addition to these global factors, specific location-bound territorial characteristics also shape the spatial distribution of innovation performance. These include the presence of local institutions, accumulated skills, knowledge, and experience (Martin and Simmie 2008; Ter Wal and Boschma 2011) and spatial proximity due to agglomeration, which can facilitate, among other things, face-to-face meetings, knowledge spillovers and collaborations (Cooke, Heidenreich, and Braczyk 2004; Storper and Venables 2004; Leamer and Storper 2014). The relative strength of global and territorial factors is likely to vary between sectors depending on their knowledge base, cluster structure, global knowledge networks, value chains, and other sector-specific innovation characteristics (Pavitt 1984; Archibugi and Iammarino 2002; Iammarino and McCann 2006; Asheim et al. 2007; Alkemade et al. 2015). It may also depend on the type of innovation activity that is taking place during different phases of the industry life cycle (e.g. development of new products or optimization of existing products and processes) (Audretsch and Feldman 1996a; Martin and Sunley 2011; Tavassoli 2015). In this sense the cluster characteristics and innovation performance of technology clusters is shaped by regional, national, and sectoral innovation systems (Nelson and Rosenberg 1993; Breschi and Malerba 1997; Cooke, Heidenreich, and Braczyk 2004; Binz and Truffer 2017).

Before considering the factors that influence innovation performance, the dynamic global spatial distribution of sustainability technology clusters is described based on a new methodology aimed at identifying sustainability technology clusters. In terms of the spatial dynamics of clusters and innovation performance, an increasing number of R&D locations are found in East Asia while some other regions of the world, notably parts of Europe, are experiencing a relative decline in innovation activity (Dicken 2007; Malecki 2014; Miao et al. 2018). However it is not clear whether this shift applies equally to all sectors, and whether the health technology and sustainable energy technology sectors are part of such a shift. This lack of information about the sustainability technology sectors leads to the formulation of the first research sub-question and supporting sub-questions:

Research Sub-question 1: What is the global spatial distribution of sustainability technology clusters and how has it changed in recent years? **Supporting sub-question 1.1:** How can sustainability technology clusters be identified on a global scale? **Supporting sub-question 1.2:** Where are the largest sustainability technology clusters located during different periods? **Supporting sub-question 1.3:** Where are growing and shrinking sustainability technology clusters located?

Aside from differences in spatial distribution, sectors can also have distinct agglomeration and knowledge network patterns (Iammarino and McCann 2006; Alkemade et al. 2015). These patterns include the degree of spatial concentration within clusters (Ter Wal and Boschma 2011) and the density and reach of knowledge networks (Alkemade et al. 2015). However, knowledge about these characteristics in specific industry sectors such as health technology and sustainable energy is limited and is therefore addressed with the second research sub-question and supporting sub-questions:

Research Sub-question 2: What are the agglomeration and knowledge network characteristics of sustainability technology clusters and how have they changed in recent years? **Supporting sub-question 2.1:** What are the clustering rates and average cluster size? **Supporting sub-question 2.2:** What is the density and reach of knowledge network links?

A deeper understanding of the spatial distribution and cluster characteristics of the sustainability technology sectors lays the foundation for analyzing the association between these characteristics and cluster innovation performance. Research sub-questions 3-6 explore the agglomeration, national innovation system, global knowledge network and path dependence characteristics of clusters.

Agglomeration characteristics appear to have a complex association with innovation performance. Clusters can experience economies of scale, but diseconomies can also arise, especially if clusters are located in large cities (Martin and Sunley 2003; Giuliano, Kang, and Yuan 2019). Large clusters located in relatively small cities (regional specialization) also experience certain advantages and disadvantages (Marshall 1920; Jacobs 1969; Tödtling and Trippl 2005). Although there is agreement in the literature that a minimum amount of agglomeration (absorptive capacity) of local firms and R&D capabilities is beneficial (Cooke 2007; Martin and Sunley 2011; Trippl et al. 2015), the scale and type of agglomeration, its importance to cluster innovation performance and sectoral differences are not well understood. These knowledge gaps are the focus of research sub-question 3 and its supporting sub-questions:

Research Sub-question 3: To what extent can the agglomeration characteristics of a technology cluster be associated with its innovation performance? **Supporting sub-question 3.1:** To what extent can agglomeration economies be associated with cluster innovation performance? **Supporting sub-question 3.2:** To what extent can regional specialization be associated with cluster innovation performance? **Supporting sub-question 3.3:** To what extent can corporate research (as a proxy for absorptive capacity) be associated with cluster innovation performance?

From a spatial perspective the national innovation system is also considered to be an important facilitator of cluster innovation performance because national innovation policies, actors, regulations, and shared cultural practices can influence innovation performance (Lundvall 1992; Nelson and

Rosenberg 1993). In Europe, China and Taiwan, among other places, there is a trend of national innovation policy programs at the regional cluster level, sometimes referred to as "smart specialization" (Su and Hung 2009; European Commission 2014a; Berger and Lester 2015). Recently, the influence of the national innovation system has been questioned and is seen to be declining due to rapid economic and technological globalization (Strange 1996; Locke and Wellhausen 2014). In the fourth research sub-question, the relevance of the national innovation system for cluster innovation performance is explored:

Research Sub-question 4: To what extent does the quality of the national innovation system influence cluster innovation performance?

Some of the advantages and disadvantages of agglomeration ("spatial proximity") noted earlier also appear to exist in the external knowledge networks of clusters. This notion gives rise to the concept of "relational proximity": a kind of non-spatial agglomeration effect. Relational proximity describes how innovation actors are connected to partners outside the cluster in relationships that involve the transfer and co-creation of knowledge and which span a range of different institutional contexts, goals and power relations (Breschi and Lissoni 2001; Bathelt, Malmberg, and Maskell 2004; Asheim and Gertler 2005; Boschma 2005; Ponds, Oort, and Frenken 2009; Torre 2014). As is the case with agglomeration, the influence of relational proximity can also seem contradictory. In some instances international research collaboration has been found to weaken local research activity and interaction (Leydesdorff and Sun 2009; Kwon et al. 2012; Van Geenhuizen and Nijkamp 2012; Ye, Yu, and Leydesdorff 2013) and this has lowered the overall innovation performance of clusters (De Propris and Driffield 2005; Chang, Chen, and McAleer 2013). Therefore both economies and diseconomies of relational proximity exist.

Especially if power imbalances exist in the relationships between research actors, there is a greater likelihood of potentially negative outcomes. For example, if a multinational organization establishes or acquires remote research labs in a cluster, this can generate a "reverse" knowledge flow from the cluster whereby the benefits of knowledge spillovers and research collaboration accrue primarily to the multinational organizations' headquarters (Frost and Zhou 2005; Ambos, Ambos, and Schlegelmilch 2006). Although "reverse" knowledge flows are a concern, the presence of multinational organizations itself often signals the success of a cluster, which attracts multinational organizations in the first place (De Propris and Driffield 2005; Liu and Buck 2007). Because multinationals account for a large share of R&D expenditure in most countries (National Center for Science and Engineering Statistics 2014), their activities can have a major influence on national and cluster innovation performance. However, the extent to which patterns of inter-cluster research collaboration and knowledge flows influence cluster innovation performance is not fully understood and is explored further with the fifth research sub-question and supporting sub-questions:

Research Sub-question 5: To what extent can knowledge networks be associated with enhanced cluster innovation performance and what is the nature (positive or negative) of this association? **Supporting sub-question 5.1:** To what extent can inter-cluster research collaboration networks be associated with cluster innovation performance? **Supporting sub-question 5.2:** To what extent can inbound and outbound knowledge flows be associated with cluster innovation performance?

Agglomeration and knowledge networks tend to develop over long periods of time. As Crescenzi and Jaax (2017) and others have demonstrated empirically, past innovation performance is an important factor in explaining current innovation performance (path dependence). However, path dependence varies depending on the sector's development phase and strengthens over time as accumulated experience, skill, relationships, and reputation confer a competitive advantage (Martin and Simmie 2008). This is an area that has not been investigated previously for sustainability technology clusters and is therefore addressed in the sixth research sub-question:

Research Sub-question 6: To what extent can the path dependence characteristics of a technology cluster be associated with its innovation performance?

After exploring the association between cluster innovation performance and various cluster characteristics in research sub-questions 3-6, sectoral differences are the focus of research sub-question 7 and 8. Pavitt (1984), Asheim and Coenen (2005) and others have argued that the way in which innovation takes place in different sectors is influenced by a sector's knowledge base and market structure and its industry life cycle phase (Malerba and Orsenigo 1997; Ter Wal and Boschma 2011; Binz and Truffer 2017). Therefore, cluster characteristics that are important in a particular sector or development phase may not be significant in other sectors or development phases. Analyzing these spatial, network and innovation performance differences provides additional quantitative insights into the innovation process of these sectors which complement existing qualitative knowledge. Sectoral differences relating to the descriptive analysis of technology clusters and knowledge networks are addressed with research sub-question 7, which builds on research sub-question 1 and 2. A comparison of the cluster characteristics associated with cluster innovation performance in different sectors is the focus of research sub-question 8, which builds on research sub-questions 3-6.

Research Sub-question 7: What are the differences between the health technology and sustainable energy technology sectors against the background of other high technology sectors, in terms of their spatial distribution, agglomeration and knowledge network characteristics? **Supporting sub-question 7.1:** To what extent can sectoral differences be attributed to the sectoral knowledge base? **Supporting sub-question 7.2:** To what extent can sectoral differences be attributed to the sectoral development phase? **Supporting sub-question 7.3:** To what extent can sectoral differences be attributed to socio-technological transitions?

Research Sub-question 8: What are the differences between the health technology, sustainable energy and other high technology sectors in terms of cluster characteristics (agglomeration, knowledge network, national innovation system, and path dependence) and cluster innovation performance? **Supporting sub-question 8.1:** To what extent can differences in association be attributed to the sectoral knowledge base? **Supporting sub-question 8.2:** To what extent can differences in association be attributed to the sectoral development phase? **Supporting sub-question 8.3:** To what extent can sectoral differences be attributed to socio-technological transitions?

An overview of the chapters in which the respective research sub-questions are addressed is provided in section 1.5.

1.4 Relevance

The contributions of this dissertation are primarily in the scientific and methodological domains. The methodological contributions lie in demonstrating the usefulness of a "heat map" spatial cluster identification method, which provides novel empirical insights into the spatial distribution, agglomeration and knowledge networks of technology clusters (subsection 1.4.1). The main scientific contributions of the study lie in (i) showing that agglomeration influences cluster innovation performance differently depending on the spatial scale involved, and (ii) identifying the likely role of socio-technological transitions in explaining differences in spatial, agglomeration, knowledge network, path dependence and innovation performance patterns in the sustainable energy technology sector (subsection1.4.2). A secondary contribution of the study is in the policy domain: the methodology to identify clusters can also be used to monitor and analyze technology clusters, which could support innovation policy making (subsection 1.4.3).

1.4.1 Methodological Contributions

This main dissertation makes two methodological contributions: the first and most important, is the identification of clusters using a novel "heat map" cluster delineation method. The second is the use of indicators derived from cluster patent data to estimate a new type of knowledge production function: the cluster innovation performance model. The novelty of both approaches lies in their unique application and combination of multiple methods, combining insights from spatial analysis, network analysis and scientometric analysis.

The "heat map"-approach, also known as Kernel Density Estimation (Rosenblatt 1956; Parzen 1962), has been widely used in other disciplines such as epidemiology, archaeology and traffic safety (Bithell 1990; Baxter, Beardah, and Wright 1997; Anderson 2009). However the method does not appear to have been used with patent data, although it should be noted that Bergquist, Fink, and Raffo (2017) apply another kind of interpolation technique in their research, which is also based on the spatial analysis of patent data (Bergquist, Fink, and Raffo 2017). In addition to the interpolation technique, the cluster delineation method used in this study also uses a single patent database, which ensures that the patent evaluation criteria are standardized (Laurens et al. 2015; Toivanen and Suominen 2015). A correction factor is also applied in this study to adjust for the home-bias effect that arises by using a national patent database (Bacchiocchi and Montobbio 2010).

The current method has four main advantages: (i) technology clusters can be identified based on real innovation data (patents) rather than using pre-existing geographic boundaries, (ii) the method can be used to identify technology clusters from broad or niche industry sectors, as long as sufficient patent data are available, (iii) a constant standard for patent evaluation across all countries is used and (iv) the criteria for identifying patents can be adjusted to correct for known biases such as home bias effects. The methodology also appears to be more precise: the "heat map" cluster identification method has a higher success rate (59-66%) in successfully identifying cluster patents when compared to pre-determined geographic boundaries (48%). The criterion for successfully identifying a cluster occurs when patents more than 64 km apart (40 mi) are assigned to different clusters (Alcácer and Zhao 2016).

In addition to a novel way of identifying clusters, the dependent variable (citations per inventor) in the cluster innovation performance model is also novel. Citations have been used in previous research to measure the quality of knowledge output (Hall, Jaffe, and Trajtenberg 2005; Waltman et al. 2012), but they have not been used in knowledge production-type functions, in which *patent count* data have typically been used. The use of citations provides insight into the quantity *and value* of knowledge produced in the cluster and it is an improvement compared to patent counts. The use of patent counts is problematic because most patents are rarely or never cited, while the most highly-cited patents describe critically important innovations in their respective industry sectors (Yang, Qian-nan, and Ze-yuan 2008). In this regard, patent citations are a more suitable measure of innovation performance.

1.4.2 Scientific Contributions

This study makes notable scientific contributions in two areas: first, the study shows that there are differences in the association (positive or negative) between cluster innovation performance and agglomeration at different spatial scales. The second scientific contribution is clear evidence of sectoral differences which can be attributed to a sector's role in socio-technological transitions (Geels et al. 2011; Ter Wal and Boschma 2011; Geels 2012; Frenken, Cefis, and Stam 2015). The findings are based on the statistical analysis of a global dataset of sustainability technology clusters whose implications are briefly discussed here.

Overall, the research results show both positive and negative associations between innovation performance and certain cluster characteristics. Agglomeration indicators (cluster size, regional specialization, and corporate research), knowledge inflow and outflow, and past innovation performance are positively associated with cluster innovation performance. The national innovation system is also positively associated with cluster innovation performance, but this association is only statistically significant in the sustainable energy sector. A negative association is observed for adjacency and the relative size of the research collaboration network. These negative associations are found in mature sectors and they are in line with relatively recent research showing that agglomeration and knowledge networks can act as barriers to innovation performance, only contribute positively under specific circumstances, or only benefit specific firms (Suire and Vicente 2009; Potter and Watts 2010; Lee 2018; Capone, Lazzeretti, and Innocenti 2019; Tomás-Miquel, Molina-Morales, and Expósito-Langa 2019). In particular, the results show that agglomeration economies exist within the local cluster, but that diseconomies of scale exist in mature sectors at a regional level (distance of up to 200 km from the cluster). In a similar way knowledge inflow and outflow appear to be positive, but clusters with large research collaboration networks relative to their size, appear to be less able to benefit from these knowledge flows.

There is also a significant difference between the spatial distribution, agglomeration, and knowledge network characteristics of the sustainable energy sector compared to other high technology sectors. The sustainable energy sector is growing rapidly both in total innovation output and the number of clusters, and the sector typically has smaller clusters and a less dense knowledge network. As a result, the sector shows no evidence of agglomeration diseconomies or a saturation of its knowledge network acting as barriers to innovation performance. These observations fit with the classification of the sustainable energy sector as an emerging sector in which agglomeration and knowledge networks are less developed (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). The sustainable energy sector also shows weaker model estimation results for path dependence compared to other sectors. This outcome could be related to the sector's involvement in a socio-technological transition. The weakness of path dependence in the sustainable energy sector suggests that the socio-technological transformations in which the sector is involved are of a greater magnitude than those of the health technology sector, where path dependence has a stronger influence on cluster innovation performance. Geels et al. (2011), Geels (2012) and others have noted the importance of subsidies, the local regulatory environment and the presence of early adopters as key factors in the development of sustainable energy technology clusters. However, these factors are not explicitly incorporated into the innovation performance model used in this study.

1.4.3 Policy Relevance

The policy relevance of this study are related to the application of the cluster identification methodology, and the descriptive and explanatory analysis based on it. The results concerning policy relevance are of an exploratory nature.

The cluster identification methodology can be used to map and monitor the development of technology clusters worldwide. From a practical perspective this information can be used for forecasting, seeking new research collaboration partners or identifying sources and destinations of R&D investment. An important advantage of the cluster identification methodology is that it can be updated regularly with new patent data and can be applied to a wide range of sectors. At a more fundamental level, because the identification of clusters is based on real innovation activity (measured through patents), the perception of clusters in terms of their size and governance, can be changed. A cluster identified from real innovation activity may "fit" within the administrative boundaries of a city, or it may be located in multiple cities, regions or even multiple countries. Especially in the case of trans-boundary clusters new collaborative approaches to cluster governance may yield positive results (Park 2014). Identifying clusters in a new way may therefore changes the local and regional perception of clusters among policy makers and cluster stakeholders.

Furthermore, the descriptive analysis in this study is relevant for cluster policies aimed at growth, while the explanatory analysis applies to policies aimed at raising cluster innovation performance (Njøs and Jakobsen 2016). The policy suggestions focus mainly on the regional level and are made from an evolutionary innovation perspective because of the theoretical framing of the research. Alongside this regional focus, national policies appear to play an important role in the growth of technology clusters in countries such as China, South Korea, and Taiwan. The research results can be used to analyze policies that promote local agglomeration, knowledge network creation, and private sector R&D investment and could support the development of national and pan-European innovation policies such as Horizon 2020 and smart regional specialization strategies.

1.5 Research Approach and Dissertation Outline

The research in this dissertation consists of two main parts: a methodological part and an empirical part. The methodological part involves identifying technology clusters and sectors, defining cluster innovation indicators, and developing the cluster innovation performance model (elaborated in chapter 3 and 4). Although the methodology builds on earlier research, its application and the combination of different steps is new. Important choices about the use of data and methodological nuances are carefully evaluated. The weaknesses of using scientometric data are discussed and mitigated as much as possible, for example by the introduction of home bias correction factors. Calibrations are carried out to optimize both the cluster identification methodology and the cluster innovation performance model. In this way a complete methodology is described that converts raw patent data into a global database of sectoral technology clusters and innovation indicators, which fills an important knowledge gap (objective 1). An overview of the chapter outline is shown in figure 1.1. The first three chapters of the dissertation cover the introduction (this chapter), an overview of key concepts and relevant theory (chapter 2), an overview of the data and methodology (chapter 3). Chapter 4 addresses the cluster identification methodology in more detail, including data, methodological choices and calibration.

Based on a solid methodological foundation laid in chapters 3 and 4, chapters 5 and 6 provide an in-depth analysis of the spatial distribution, knowledge networks and cluster innovation performance of health technology and sustainable energy technology clusters. This analysis touches upon global shifts in innovation activity (Dicken 2007), the roles of various kinds of spatial and relational proximity (Boschma 2005), and their association with cluster innovation performance and the sectors' path dependence (Martin and Simmie 2008). Research sub-questions 1-6 are answered in these chapters for each particular sector.

Chapter 7 provides a comparison of the health technology and sustainable energy technology sectors, which is benchmarked against aggregate data of other high technology sectors. This comparison seeks to understand the differences between the sustainability technology sectors and other high technology sectors, including the sectors' development phase and knowledge base (Ter Wal and Boschma 2011; Binz and Truffer 2017). Research sub-questions 7 and 8 are answered in this chapter.

The combination of a novel methodology, diverse theoretical perspectives, and the empirical results for two important sustainability technology sectors provide a strong basis for discussion and reflection in the final chapters of the dissertation. Chapter 8 serves to combine and reconcile the different findings of the earlier chapters and provides a review of existing theory, which is assessed against the new methodology and empirical insights gained from the research. Chapter 9 concludes with some reflections, a list of key findings and recommendations for future research.

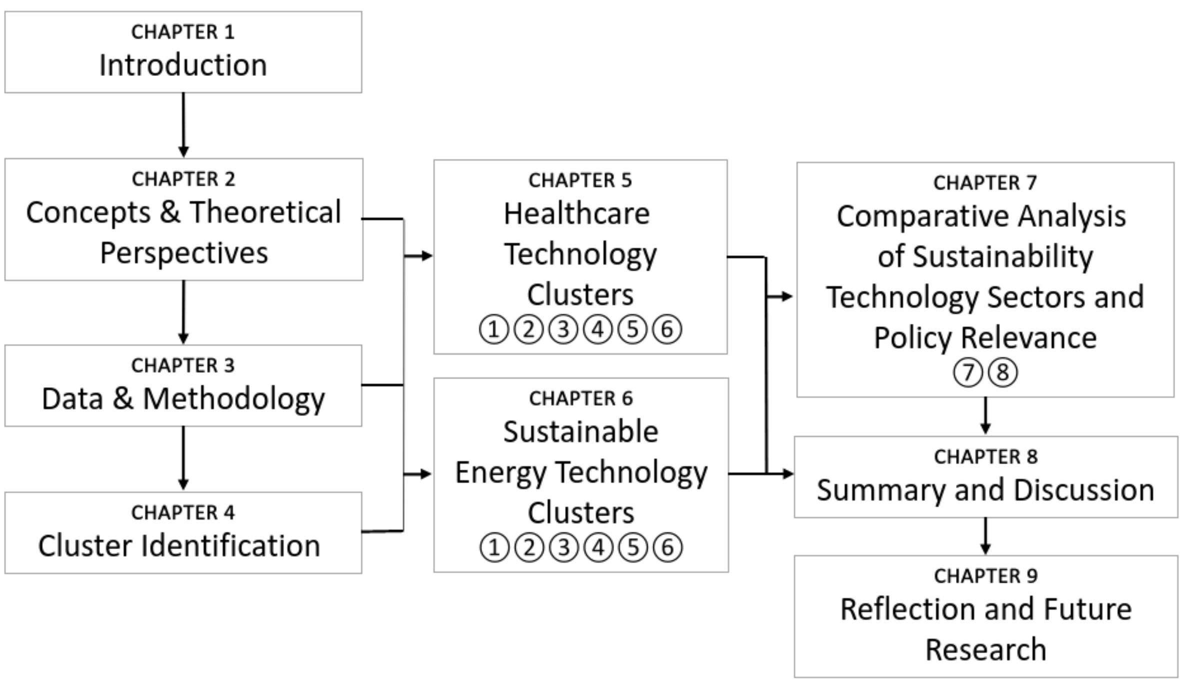

Figure 1.1: Chapter outline, research sub-questions addressed in each chapter are indicated in circles.

Chapter 2

Concepts and Theoretical Perspectives

2.1 Introduction

This chapter provides an overview of the main concepts, theories and hypotheses related to the study questions raised in this dissertation. The chapter begins with a discussion of three core concepts: innovation performance, technology clusters, and socio-technological transitions (section 2.2), which lay a foundation for the discussion of the theory and the formulation of related hypotheses. The theory is discussed in two parts. First, the spatial distribution and knowledge network patterns of technology clusters are discussed (section 2.3, related to research questions 1, 2 and 7). Next, the conditions associated with cluster innovation performance are addressed, including the role of agglomeration, national innovation systems, knowledge networks, and path dependence (section 2.4, related to research questions 3-6 and 8). The chapter concludes with a summary and discussion of the main theoretical ambiguities uncovered during the literature review (section 2.5). For reference purposes a list of selected terminology is also included at the end of the chapter (section 2.6).

2.2 Core Concepts

The three core concepts presented here form the building blocks for understanding the theoretical perspectives presented in this study. The concepts are: innovation performance (subsection 2.2.1), technology clusters (subsection 2.2.2), and socio-technological transitions (subsection 2.2.3). Innovation performance is important because innovation brings economic, societal and sustainability benefits (Schumpeter 1934; Tidd, Bessant, and Pavitt 2005; Rauter et al. 2019). Technology clusters are an important spatial unit in which innovation activity and important actor interactions take place which influence innovation performance (Marshall 1920; Nooteboom 2006; Porter 1998). Finally, socio-technological transitions are seen as a defining feature of the sustainable energy technology sector (Geels et al. 2017) and to a lesser extent, the health technology sector (Ohta 2019). As a theoretical concept socio-technological transitions are relatively new, yet they are seen as having a deep influence on many different aspects of innovation performance. Other concepts and terminology are briefly defined at the end of this chapter, in section 2.6.

2.2.1 Innovation Performance

In this subsection the concept of innovation performance is defined, followed by a brief discussion of the main challenges to achieving high innovation performance. As noted in the first chapter, innovation performance can be concisely defined as the ability to generate new knowledge and apply it in *an economically useful way* (Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005). As the American inventor Thomas Alva Edison once said: "innovation is more than simply coming up with good ideas; it is the process of growing them into practical use" (Tidd, Bessant, and Pavitt 2005, 66). "The real challenge in innovation [is] not invention - coming up with good ideas - but in making them work technically and commercially" (Tidd, Bessant, and Pavitt 2005, 65). This view is shared by Schumpeter (1934), Drucker (1985) and others who note that innovation includes both the generation of new knowledge (invention) and its application in ways that deliver economic and societal benefits (Tidd, Bessant, and Pavitt 2005; Hirshleifer 1971). Rauter et al. (2019) have also noted the sustainability benefits of innovation.

Innovation, like invention, can be undertaken by an individual, but is usually undertaken by groups of people, who may be affiliated to different organizations. Hence innovation is often viewed as a social process, and as a result, inter-organizational collaboration, the functioning of teams, and inter-personal and inter-organizational relationships are emphasized in the research (Nonaka 1991; Dodgson 1994; Tidd, Bessant, and Pavitt 2005; Chesbrough 2006). From an economic perspective, firms, and national governments tend to be dominant organizations in the innovation process, because they account for most R&D expenditure (approximately 63-69% by business and 25-30% by government in the United States, according to National Center for Science and Engineering Statistics (2014)). The financial control of innovation by business and government ensures that these actors play an important role in deciding the direction of innovation strategies (Teece, Pisano, and Shuen 1997; Porter 1998; Brenner and Schlump 2011; Casper 2013), although research collaborations between industry, universities, and governments are also seen as important (Nelson and Rosenberg 1993; Etzkowitz and Leydesdorff 2000; Etzkowitz and Zhou 2019).

Managing innovation is challenging for a variety of reasons, of which the following three are seen as most prominent. First, the complexity of advanced technology requires collaboration between researchers with different expertise and who may work for different organizations, creating potential cognitive, inter-organizational, and inter-personal challenges (Dodgson 1994; Chesbrough 2006). Second, the tacit nature of knowledge creation requires collaboration and trust between researchers, but also openness to new ideas, characteristics that can be difficult to balance within a research team (Nonaka 1991; Barjak and Robinson 2008; Nooteboom 2013). Third, persons and organizations involved in innovation need to overcome both technological and market uncertainties: they cannot know beforehand if a new technology will work and they are also unsure about its market acceptance and commercial viability (Hirshleifer 1971; Tidd, Bessant, and Pavitt 2005). Innovation is a delicate process that only succeeds if multiple conditions align favorably.

The challenges of managing innovation can be even greater in sectors such as the medical life sciences which are structurally high-risk (and high-reward). Booth (2016) notes that the medical life sciences innovation is especially high-risk because of a dependence on cutting-edge basic research (new technologies) and the importance of medical trials prior to the commercialization of a new product (uncertain market entry). A different kind of innovation risk exists when innovations involve changes in socio-technological systems because they bring about (or require) disruptions of existing markets, technologies, and business models (Tidd, Bessant, and Pavitt 2005; Geels et al. 2011; Geels 2012). Spatial and relational proximity, among other factors, can help mitigate some of these risks and lower barriers for knowledge transfers. Spatially concentrated technology clusters with a dense network between different actors can therefore enable high innovation performance (Porter 1998; Nooteboom 2006; Feldman and Kogler 2010; Panetti et al. 2020).

2.2.2 Technology Clusters

Technology clusters are an important spatial phenomenon in the innovation literature (Feldman and Kogler 2010) even though controversy remains about their precise role and influence on innovation performance (Martin and Sunley 2003; Crescenzi et al. 2019; Vaan, Frenken, and Boschma 2019). In this study a technology cluster is defined as a spatial concentration of R&D and innovation activity related to a particular industry sector (Feser and Luger 2003; Lange 2016). The *technology* cluster concept is defined by comparing it to the older and more established concept of an *industry* cluster in the next paragraph (Porter 1998; Feser and Luger 2003; Nooteboom 2006).

More than a century ago Marshall (1920) defined industrial districts (clusters) as "concentration of specialized industries in particular localities" (p. 25), which offer a number of specialization advantages to firms located there. Nooteboom (2006) offers a more precise definition of industry clusters as "geographically proximate firms in vertical and horizontal relationships involving a localized enterprise support infrastructure with shared developmental vision for business growth, based on competition and cooperation in a specific market field" (p. 156), and notes the tendency for competitive and collaborative behavior between firms within a cluster. In addition to spatial proximity and interactions between firms, another feature of clusters is the presence of different types of organizations which are also seen as a part of the cluster. According to Porter (1998):

> many clusters include governmental and other institutions - such as universities, standards-setting agencies, think tanks, vocational training providers, and trade associations - that provide specialized training, education, information, research, and technical support. (p. 3)

A technology cluster is seen as a special type of industry cluster which contains R&D and innovation activities. These R&D and innovation activities are often located together with other industry functions such as manufacturing, testing, packaging, distribution, marketing, etc. in a broad-based industry cluster, however this is not always the case. Innovation can also be spatially distant from other industry activities such as manufacturing, which is the case in the hard disk drives (McKendrick, Doner, and Haggard 2000) and wind turbines industries (Awate, Larsen, and Mudambi 2012). In the case of the hard disk drive industry, in the 1980s and 1990s McKendrick, Doner, and Haggard (2000) note that technology clusters (with R&D) were located primarily in Japan and the United States, while manufacturing clusters (with no or limited R&D) were found mainly in Thailand, Malaysia and Singapore. The spatial patterns of R&D and production are dynamic, and more recently there has been a trend of "offshoring" certain R&D activities to emerging economies, notably China and India (Bruche 2009).

As noted earlier, the spatial proximity of innovation actors within technology clusters can facilitate social interactions and inter-organizational relationships (Porter 2000; Malmberg and Maskell 2002; Gertler and Levitte 2005; Nooteboom 2006). These interactions include research collaboration and learning (Porter 1998), and stimulating competitive drive between firms and researchers (Porter 2000; Malmberg and Maskell 2002). However, spatial proximity alone does not bring about social interactions and inter-organizational relationships, and therefore the precise role of technology clusters is frequently questioned (Frenken, Cefis, and Stam 2015; Moretti 2019; Kemeny and Storper 2020).

2.2.3 Socio-Technological Transitions

Innovation can be influenced by societal, economic, technological, and policy factors, making it a central part of broader socio-technological (or sustainability) transitions (Geels et al. 2017; Ohta 2019). Understanding the influence of socio-technological transitions on cluster innovation performance in the health technology and sustainable energy technology sectors is one of the main research gaps addressed in this dissertation. The concept of socio-technological transitions is explored by comparing how innovation during socio-technological transitions differs from "normal" innovation, which is primarily technological in nature.

While "normal" innovation research often focuses on the role of firms and the market, innovation in the context of socio-technological transitions tends to involve many different actors, such as civil society groups, media, regulators, and policy makers (Geels et al. 2011; Geels 2012). A prominent example of a current socio-technological transition is the shift towards low-carbon energy and transportation systems, which is a matter of great social and political urgency (Intergovernmental Panel on Climate Change 2015; Geels et al. 2017). Geels et al. (2017) observe that the successful adoption of low-carbon technologies depends on the power of civil society, media, government (at various levels), regulatory bodies, financial investors, political parties, and advisory bodies, in addition to the actions of consumers and firms. All actors who may, or may not, have vested interests. The involvement of multiple actors means that transition-supporting innovations also need to meet multiple objectives and face multiple barriers and constraints. Competing objectives can include cost-effectiveness, fairness, social and political acceptance, and consumer preferences. This complex innovation environment not only requires competent internal innovation management but also resilience in the face of occasional set-backs or shifts in support, and flexibility in establishing partnerships and accommodating multiple goals (Geels et al. 2017).

The growth of technology clusters that are part of a socio-technological transition can be enabled by specific social, economic, and political conditions (Coenen, Benneworth, and Truffer 2012). Conditions include supportive government policies, community receptiveness to new technologies and lifestyles, and the presence of early adopters (Coenen, Benneworth, and Truffer 2012; Geels 2012; Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Ye 2018). In addition, a protected niche for experimentation can help new technologies overcome initial barriers by protecting them against competition by incumbent technologies (Sengers and Raven 2015; Raven et al. 2016; Steen and Hansen 2018; Langhelle, Meadowcroft, and Rosenbloom 2019). Technology clusters involved in socio-technological transitions are therefore likely to emerge in cities or countries that provide these conditions (Truffer, Murphy, and Raven 2015; Vaan, Frenken, and Boschma 2019).

Although the concept of socio-technological transitions is often applied to sustainable energy technology sectors (Geels et al. 2017; Langhelle, Meadowcroft, and Rosenbloom 2019), healthcare sectors are also seen as undergoing sustainability transitions. Healthcare innovation involves a diverse stakeholder landscape of firms, patients, (academic) hospitals, regulators, healthcare and insurance providers, community and family members and research institutions, who all have different, and at times competing, priorities and limitations (Gelijns and Thier 2002; OECD 2017; Lopes et al. 2019). Major changes to the healthcare system are a response to a demographic transition (ageing population) and to the social wishes of keeping healthcare affordable and inclusive. They can all be seen as part of a socio-technological transition that poses innovation and governance challenges (Ohta 2019).

2.3 Global Spatial Distribution of Technology Clusters and Knowledge Networks

In this section the theory related to the global spatial distribution of technology clusters and their knowledge networks are discussed, which relate to research question 1, 2, and 7. Research question 1 concerns the global spatial distribution of health technology and sustainable energy technology clusters and the likely locations of growing and declining clusters. It is addressed in subsection 2.3.1. Research question 2 is concerned with spatial concentration (agglomeration) and knowledge network structure (such as the network density) of technology clusters, and research question 7 explores sectoral differences in spatial distribution, agglomeration, and knowledge networks. Research questions 2 and 7 are addressed in subsection 2.3.2. All three research questions are descriptive in their focus. For this reason the theory presented here covers general patterns and influences while also noting the possible effects of socio-technological transitions on technology clusters.

2.3.1 Dynamic Spatial Distribution of Technology Clusters

Innovation activity has two important spatial features, which at first can seem contradictory: innovation activity is globally distributed but also spatially concentrated in a relatively small number of locations worldwide (Feldman and Florida 1994; Storper 1997; Malecki 2014; Crescenzi et al. 2019). These locations are connected through knowledge networks (Fischer and Varga 2003; Ó hUallacháin and Lee 2014). Viewed from the perspective of globalization, innovation activity can be footloose and globally mobile, constantly seeking the best ideas and talent at the lowest cost (Strange 1996; Locke and Wellhausen 2014), giving rise to global knowledge networks (Fischer and Varga 2003; Ó hUallacháin and Lee 2014). Viewed from the perspective of agglomeration, the spatial concentration of innovation activity in technology clusters suggests that territorial advantages, including physical proximity, also influence the creation and growth of clusters (Bathelt, Malmberg, and Maskell 2004; Gertler and Wolfe 2006; Binz and Truffer 2017).

The spatial dynamics of technology clusters can be divided into two types of movement: shifts occurring in *established* sectors and the rapid growth of technology clusters from *newly emerging* sectors. One of the most significant spatial shifts that has occurred in recent decades is the global shift of innovation activity from certain parts of North America, Western Europe, and Japan towards certain countries in Asia (Hobday 1995; Koh and Wong 2005; Dicken 2007; Miao et al. 2018). This global shift is ongoing and is driven by several interrelated factors. An important "pull" factor are investments in R&D, education, and other knowledge infrastructure in (mainly) Asian countries (Amsden 2001; Dicken 2007). These in turn have encouraged multinational corporations to transfer high value-added activities, including R&D, to countries such as India and China, in order to access a large, lower cost, and highly educated talent pool, a process often referred to as "offshoring" (Kojima 2000; Dicken 2007; Bruche 2009; Nieto and Rodríguez 2011; Crescenzi and Rodríguez-Pose 2017). In addition to multinational corporation-driven transfers, a number of Asian countries such as Singapore, South Korea, Taiwan, and China have also successfully implemented national R&D strategies to develop their domestic high technology industry (Hobday 1995; Lee and Lim 2001; Koh and Wong 2005; Dicken 2007; Lee, Tee, and Kim 2009; Joo, Oh, and Lee 2016; Miao et al. 2018). To illustrate the magnitude of the global shift in innovation activity to Asia note that the relative share of global R&D performed in the European Union has declined from 26% in 2001 to 22% in 2011 and the share of the United States has declined from 37% 2001 to 30% in 2011 (National Center for Science and Engineering Statistics 2014). China has seen an average annual increase in R&D activity of 18% from 2001-2011, making the United States, China, and Japan the world's three largest R&D-performing countries in 2011 (National Center for Science and Engineering Statistics 2014).[1]

Changes in global innovation activity are driven by a number of different factors, including at the cluster-level. The creation of new clusters, whether from established or newly emerging sectors, is frequently linked to policy interventions. This is a key finding in studies of late-industrializing countries in East Asia such South Korea or China which have successfully developed high technology industries (Lee and Lim 2001; Naughton 2007; Su and Hung 2009). It is also suggested in case studies of newly emerging sectors, such as sustainable energy technology clusters, in advanced industrialized countries in Europe and North America (Holbrook, Arthurs, and Cassidy 2010; Steen and Hansen 2018; Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Ye 2018). In sustainable energy technology clusters government policies at different spatial levels can create the necessary support, or a protected niche, for experimentation and further development of a technology to take place (Sengers and Raven 2015; Raven et al. 2016; Langhelle, Meadowcroft, and Rosenbloom 2019). Although the technological and business context of high technology catching-up and the creation of new-to-world sustainable energy technology clusters is very different, policy interventions seem to play an important role in both situations (Lee and Lim 2001; Coenen, Benneworth, and Truffer 2012; Truffer, Murphy, and Raven 2015; Miao et al. 2018). New technology clusters, whether from catching-up of emerging sectors, benefit from measures such as public co-investment in R&D, the presence of supportive local launch customers, favorable regulations, and tax incentives which help firms, or groups of related firms, overcome initial development barriers (Kim and Lee 2008; Su and Hung 2009; Holbrook, Arthurs, and Cassidy 2010; Steen and Hansen 2018).

In addition to policy interventions, new clusters can also be created due to chance, a series of unplanned but fortunate events that led to positive outcomes, which give rise to a new technology cluster. Specific triggers such as layoffs of researchers, or the reverse, the appointment of a key professor at a university or the winning of a competitive research grant, often play a crucial role in a technology cluster's establishment and early growth (Feldman, Francis, and Bercovitz 2005; Isaksen 2016; Crescenzi et al. 2019). These events may not always occur as part of a concerted policy effort to develop a cluster, but they can nevertheless play a very important role. Although it must be noted that the identification of such events is often much easier with the benefit of hindsight (Isaksen 2016). Furthermore, the occurrence of such an event, which may lead to the early development of an industry in a particular location, does not guarantee its long-term development and growth (West 2014).

Because the global shift of R&D towards Asia is ongoing, often accompanied by government policies promoting R&D investment, it is likely that new and fast-growing health technology and sustainable energy technology clusters are found in this part of the world. However, it must be

[1] The empirical research presented in this study also covers the 2000-2011 period.

noted that the increase in R&D expenditure has not been shared equally across countries in Asia. The majority of R&D expenditure takes place in China, India, Japan, Malaysia, Singapore, South Korea, and Taiwan, which together accounted for 34% of global R&D output in 2011 (National Center for Science and Engineering Statistics 2014). For this reason new and fast-growing technology clusters are likely to be found more often in these Asian countries, as summarized in hypothesis 1.

Hypothesis 1: New and fast-growing sustainability technology clusters are more frequently located in Asia.

2.3.2 Sectoral Differences in Agglomeration and Global Knowledge Networks

In addition to *where* technology clusters are located, their size, and global knowledge network characteristics also vary considerably. Sectoral differences in technology cluster agglomeration and global knowledge network patterns are typically explained from two perspectives: the knowledge base of the sector and ease of knowledge transfer (Carlsson 2013; Battistella, De Toni, and Pillon 2016; Jeannerat and Kebir 2016; Fabiano, Marcellusi, and Favato 2020), and its development phase (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). Both perspectives are considered here.

The knowledge base of a sector is seen to exist on a spectrum between two extremes: a scientific knowledge base and an engineering and design knowledge base. In sectors with a scientific knowledge base innovation primarily takes place through the application of new scientific discoveries. The ease with which scientific knowledge can be codified enables collaborations over longer distances (Stankiewicz 2002; Carlsson 2013). Sectors such as biotechnology, chemicals, pharmaceuticals, and micro electronics are typically seen as having a more scientific knowledge base (Tidd 2001). Sectors with an engineering and design knowledge base, such as automobiles and machinery, innovate based on interactions with customers and suppliers, and through "learning by doing," enabling the accumulation of experience and specialized skills (Jeannerat and Kebir 2016). In these sectors the importance of tacit knowledge and inter-personal interaction is typically emphasized (Nonaka 1991; Stankiewicz 2002; Gertler 2003) and therefore these sectors should benefit more from spatial proximity which can enable more frequent personal interactions (Stankiewicz 2002; Asheim and Coenen 2005; Carlsson 2013).

These characteristics can be extrapolated towards differences in agglomeration and knowledge networks between sectors. The codified knowledge of sectors with a scientific knowledge base could lead to more frequent global knowledge network linkages, something which has been noted in the literature, specifically for healthcare sectors (Alkemade et al. 2015). If codified knowledge is related to more frequent global network linkages, it could be argued that the tacit knowledge of sectors with an engineering and design knowledge base generates fewer global linkages. Instead these sectors may have more local linkages, which increases the importance and scale of spatial agglomeration in these sectors.

In reality such a binary explanation could be an oversimplification. For example, interpersonal interaction needed for tacit knowledge transfers can also be facilitated at a distance through conferences, frequent visits and teleconferencing, especially if participants share a common culture and goals, such as being members of the same multinational corporation (Gertler 2003; Maskell, Bathelt, and Malmberg 2006; Henn and Bathelt 2015; Comunian 2017). Furthermore, cluster formation in sectors with a scientific knowledge base can occur for reasons other than facilitating interpersonal interactions, such as the local availability of talent and access to research at universities (Anselin, Varga, and Acs 1997; Florida 1999; Casper 2013). This makes it very difficult to predict the agglomeration or knowledge network characteristics of technology clusters based on their sectoral knowledge base, and a developmental perspective may be more valuable.

Viewed from the developmental perspective of technology clusters and sectors, spatial concentration increases over time because growth in R&D activity tends to occur in existing clusters, thus increasing the spatial concentration of the sector as it matures (Crescenzi and Rodríguez-Pose 2011; Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). A cluster's global knowledge network also tends to become denser as a sector matures (Su and Hung 2009; Ter Wal and Boschma 2011). For this reason a sector in an early development phase is likely to have smaller clusters and a less dense knowledge network as compared to a more mature sector, although its clusters and knowledge networks may be growing rapidly (Klepper 1997; Ter Wal and Boschma 2011). If the health technology sector is seen as a mature sector and the sustainable energy technology sector is seen as an emerging sector, then it is likely that health technology clusters have a denser knowledge network and a higher rate of spatial concentration than sustainable energy technology clusters. Hypothesis 2 is therefore as follows:

Hypothesis 2: The health technology sector has a denser knowledge network and a higher rate of agglomeration than the sustainable energy technology sector.

2.4 Cluster Innovation Performance Conditions

In this section the theory related to cluster innovation performance and its associated cluster characteristics is addressed, covering research questions 3-6 and 8. The cluster characteristics associated with cluster innovation performance can be divided into four groups: agglomeration, the national innovation system, knowledge networks, and path dependence. These cluster characteristics are consistently cited in the literature, although the terminology and theoretical background varies, and debate exists about the direction (positive or negative) and importance of certain cluster characteristics. In fact, each of the four groups mentioned has at least one point of notable theoretical ambiguity. To briefly summarize: (i) agglomeration is often positively associated with cluster innovation performance, however in very large clusters diseconomies of scale can arise due to competition, congestion, and higher costs (Martin and Sunley 2003). (ii) The extent to which the national innovation system influences cluster innovation performance is unclear (Strange 1996; Dicken 2007; Binz and Truffer 2017). (iii) Global knowledge networks are seen to enhance a cluster's access to knowledge, but they may also lead to knowledge outflow (Frost and Zhou 2005; Ó hUallacháin and Lee 2014). (iv) Path dependence can lead to contradictory outcomes: on one hand, the accumulation of skills, knowledge, and experience can lead technology clusters to persistent high innovation performance over long periods of time, but it can also trap clusters into an out-dated technological development path that leads to their long-term decline (Martin and Simmie 2008; Crescenzi and Rodríguez-Pose 2011; Østergaard and Park 2015; Trippl et al. 2015). Each of these points is discussed in detail in the subsections that follow (2.4.1-2.4.4). These discussions addresses research questions 3-6 (agglomeration, national innovation system, knowledge networks, and path dependence).

Research question 8 specifically addresses the notion that sectoral differences are a moderating factor between cluster characteristics and cluster innovation performance. As the discussion about sectoral differences in cluster characteristics in subsection 2.3.2 showed earlier, there is only a very limited theoretical basis in this area. For this reason sectoral differences are only addressed in subsection 2.4.4 alongside path dependence. Strong path dependence is typically seen as a characteristic of a mature sector, whereas emerging sectors have weaker path dependence (Martin and Simmie 2008).

2.4.1 Agglomeration

Theories of agglomeration can broadly be divided into two groups: a *quantitative* scale-based perspective (Marshall 1920) and a *qualitative* perspective which includes, for example, the diversity of local actors (Jacobs 1969), local knowledge spillovers and learning (Cooke 2007; Capello 2009), local absorptive capacity (Fu 2008; Lau and Lo 2015), and social capital and trust (Nooteboom 2013; Vaan, Frenken, and Boschma 2019).

Scale-based agglomeration theories focus on the close spatial proximity of innovation actors within a cluster, the location of clusters within major cities, and clusters being located near to each other. These spatial characteristics create a number of scale-related advantages as well as potential disadvantages, which occur at larger scales. Close spatial proximity leads to a number of agglomeration effects brought about by local specialization in a particular industry sector (Marshall 1920; Spencer et al. 2010). In this subsection these scale-based agglomeration advantages are discussed from three main dimensions: facilitating transactions and collaboration between actors, raising productivity and providing an environment with shared values, beliefs and trust (Morgan 2004; Capello 2009; Leamer and Storper 2014). This is followed by an overview of the disadvantages of scale-based agglomeration.

The first dimension of these scale-based agglomeration advantages relates to being spatially close in larger clusters which leads to potentially lower transport and transmission costs, proximity to final markets (for firms) or test/launching markets (for innovations), a larger chance for meeting of two agents, eventually leading to serendipity, and easier exchange of creative ideas (Morgan 2004). Spatial proximity also facilitates collaborative vertical interaction with local customers and producers in which learning-through-interacting generates benefits for both parties by co-creating new products and services with users (Gertler and Levitte 2005; Priem, Li, and Carr 2012; Von Hippel 1986). These interactions facilitate local knowledge spillovers between innovation actors, including through labor mobility, and enhance their overall creativity and innovativeness (Fischer and Varga 2003; Grillitsch and Nilsson 2017; Kemeny and Storper 2020). Highly creative individuals are seen as being more productive when surrounded by other high-performing peers (Moretti 2019).

The second dimension emphasizes productivity increases due to cost reductions (scale effect) and localized accumulation of production skills (Capello 2009). Spatial proximity of firms also encourages competition, and the innovative drive arising from it, stimulating firms to learn from one another through observation and monitoring, and to raise their productivity (Porter 2000; Malmberg and Maskell 2002).

A third dimension draws attention to synergy and refers to the rise of a set of common values and beliefs, which acts as the rationale for the reduction of transaction costs (Williamson 1981). The spatial proximity also facilitates risk-sharing investments, which require a large degree of trust, something that is more likely to be found inside a cluster where common conventions and norms and readily available knowledge about the reliability and trustworthiness of individual actors supports the flow of knowledge (Keeble et al. 1999; Cooke, Heidenreich, and Braczyk 2004; Storper and Venables 2004; Leamer and Storper 2014). Or, approached from the perspective of conflict avoidance: spatial proximity facilitates collaboration by being instrumental in attenuating conflicts that may arise from institutional distance (Ponds, Oort, and Frenken 2009; D'Este and Iammarino 2010).

Many scale-based agglomeration effects also apply more generally to urban areas: in major cities being spatially close can lower transport and transmission costs, provide proximity to markets, a larger chance for meeting of two agents and easier exchange of creative ideas (especially for interdisciplinary projects). This, in addition to available economies of scale, specialized business services, and a greater ability to attract talent, etc. (Florida 1999; Morgan 2004; Capello 2009). These benefits may be absent in smaller cities or less urbanized areas. On the other hand, major urban areas may suffer from a higher cost of living and lower quality of life due to congestion, diseconomies of scale and competition for resources (Richardson 1989; Zheng 2001; Martin and Sunley 2003). Large cities typically suffer from higher housing and land prices, long commuting times, higher infrastructure costs, and a low environmental quality of life (Richardson 1989; Zheng 2001).

Doubt can also be expressed over whether scale-based agglomeration has tangible benefits in terms of raising firms' innovation performance, as many of the above benefits may exist, but they are relatively insignificant compared to other conditions (Beaudry and Breschi 2003; Frenken, Cefis, and Stam 2015; Fitjar and Rodríguez-Pose 2017), or only occur once a particular scale is reached (Beaudry and Breschi 2003; Van Geenhuizen and Reyes-Gonzalez 2007). The co-location of knowledge producers is no guarantee that any local knowledge spillovers are taking place, or synergies are being realized as institutional barriers, cultural differences, or competitive strategies can prevent knowledge spillovers and research collaborations, a perspective further emphasized by the "relational" geography of innovation perspective (Boschma 2005; Cooke 2007; D'Este and Iammarino 2010; Karlsson 2010). Additionally, the over-embeddedness of firms within a cluster may cause problems, as connections within the cluster may isolate firms from emerging new knowledge outside the cluster (Tödtling and Trippl 2005; Masciarelli, Laursen, and Prencipe 2010).

In addition to the potential effects of being located in a large cluster or urban area, a neighborhood effect is frequently found in spatial economic studies because investment, markets and collaborative ties are easier to establish with adjacent or nearby clusters and regions (Giarratani, Hewings, and McCann 2013; Clark and Wójcik 2018). Prior studies specific to innovation performance have also shown that high performing neighboring regions have a positive influence on innovation performance (Ó hUallacháin and Leslie 2007; Charlot, Crescenzi, and Musolesi 2014), and that the positive effect of knowledge spillovers extend significantly beyond the boundaries of the cluster itself at scales of 80 km or more (Acs, Anselin, and Varga 2002). Ambiguity about the nature of the association between scale-based agglomeration and cluster innovation performance, including at different spatial scales, leads to the formulation of hypothesis 3. Agglomeration in hypothesis 3 refers to scale-based agglomeration of clusters (cluster size) and nearby clusters (adjacency effects). Note that the hypotheses are formulated with the term "association" and not "influence" because reverse causality between innovation performance and agglomeration is also possible: high-performing clusters may experience faster growth and hence, increased agglomeration.

Hypothesis 3: Agglomeration has a positive association with cluster innovation performance.

In addition to the scale effects of agglomeration, the *qualitative agglomeration* aspects of clusters are frequently noted in the literature. Diversity of knowledge, actors, and sectors is seen as an important source of innovation because it facilitates the cross-fertilization of ideas between different knowledge domains (Jacobs 1969; Camagni and Capello 2002; Capello 2009). Technology clusters located in larger urban centers with a diversified industrial and technological base are more likely to be able to benefit from this diversity.

On the other hand, clusters located in major urban centers, as noted earlier, may face higher operating costs, more congestion, lower quality of life, and greater competition for resources from other sectors within the regional innovation system (Zheng 2001; Martin and Sunley 2003; Tabuchi and Thisse 2006; Frenken, Cefis, and Stam 2015). So high regional specialization, which means a cluster is relatively large as compared to the regional innovation system, could raise or lower cluster innovation performance depending on the importance of, on the one hand diversity benefits, and on the other hand, higher operating costs and increased competition. This ambiguity is further explored in hypothesis 4, with the working assumption that the benefits from regional specialization outweigh the potential loss of opportunity from inter-sector knowledge spillovers.

Hypothesis 4: Regional specialization has a positive association with cluster innovation performance.

Aside from regional specialization and access to diverse local knowledge, the quality of institutions within the cluster, such as the presence of high quality university research, can positively contribute to cluster innovation performance. Spillover effects and institutionalized knowledge transfers between university-based scientific research to industry-based R&D is well known in this theoretical thinking (Henderson, Jaffe, and Trajtenberg 1998; Ponds, Oort, and Frenken 2009; Casper 2013; Qiu, Liu, and Gao 2017). The contribution of local scientific research may also be more indirect: Florida (1999) suggests that universities attract outside research talent and that this is their main contribution to a region, rather than locally generated knowledge. Outside talent contributes to a cluster's labor force, knowledge stock, and brings with them a personal network of contacts.

However, empirical evidence suggests that the presence of university and government research alone does not guarantee high cluster innovation performance (Ó hUallacháin and Leslie 2007). Regions without a significant industrial base with adequate R&D capabilities are often unable to benefit from knowledge spillovers from universities (Casper 2013; Qiu, Liu, and Gao 2017; Tomás-Miquel, Molina-Morales, and Expósito-Langa 2019). Entrepreneurial activity (Audretsch and Lehmann 2005; Feldman, Francis, and Bercovitz 2005; Acs et al. 2009; Frenken, Cefis, and Stam 2015) and private-sector research expenditure (Dosi, Llerena, and Labini 2011) were identified as important conditions for high innovation performance at a regional level. Therefore, private sector corporate research, rather than university or government research, tends to be positively associated with the innovation performance of the cluster.

Hypothesis 5: Corporate research activity has a positive association with cluster innovation performance.

2.4.2 National Innovation System

The national innovation system concept is closely related to the concept of the regional innovation system (Cooke 2007), which was discussed as part of agglomeration theory in the previous subsection (2.4.1). However, the national innovation system covers the *national* rather than a sub-national regional scale. The national innovation system was originally conceived as a constellation of three groups of actors: universities, industry, and government, each of which has specific functions (Lundvall 1992; Etzkowitz and Leydesdorff 2000). The role of universities is basic research and teaching, thus contributing to the system's knowledge base and stock of human capital. Part of this output forms part of the inputs for industry research, which is aimed at product and process improvements, and the commercialization of new technologies, contributing to firms' profitability and growth, and thus the growth of the economy (Lundvall 1992). The government acts as a regulator and invests in universities and research that it deems to be in the public interest, such as research related to national defense, public health or space exploration (Nelson and Rosenberg 1993; Fabrizio, Poczter, and Zelner 2017). There is a consensus that more balanced national innovation systems, i.e. those in which universities, government, and industry all play their part, deliver the highest innovation performance (Nelson and Rosenberg 1993; Dosi, Llerena, and Labini 2011; Khedhaouria and Thurik 2017). In addition to universities, government and industry, other factors, such as the type of regulation, and entrepreneurship and risk-taking in national culture, are also seen to influence national innovation performance (De Rassenfosse and Potterie 2009; Autio et al. 2014; Fabrizio, Poczter, and Zelner 2017).

Technology clusters exist within the context of national innovation systems, but they are also part of global sectoral innovation systems (Binz and Truffer 2017). As a result, both national and international changes in markets, policies, and technologies can influence cluster innovation performance. In recent decades the relative power of national governments and institutions has declined as a result of rapid economic and technological globalization, often supported by the policies of Western governments and institutions (Strange 1996; Dicken 2007; Locke and Wellhausen 2014). Dicken (2007) argues that a power shift in favor of multinational corporations has changed the relationship between national governments and multinational corporations, but that both are still very influential. The following hypothesis is proposed to address this ambiguity.

Hypothesis 6: The quality of the national innovation system has a positive influence on cluster innovation performance.

2.4.3 Inter-Cluster Knowledge Networks

Like agglomeration ("spatial proximity"), the conditions of global inter-cluster knowledge networks ("relational proximity") are seen as an important feature of technology clusters (Boschma 2005). The global distribution of R&D is characterized by patterns of spatial concentration, which are coupled to global inter-cluster knowledge networks (Fujita, Krugman, and Venables 2001; Gertler and Levitte 2005; Gertler and Wolfe 2006; Feldman and Kogler 2010; Malecki 2014). This subsection provides a discussion of the literature and hypotheses in two parts: the first part related to knowledge flows into and out of technology clusters, and the second part focusing on inter-cluster research collaboration networks.

Knowledge networks typically consist of some kind of collaborative relationship involving the transfer and co-creation of knowledge (Bukvova 2010). These relationships can span a range of different institutional contexts, goals and power relations (Breschi and Lissoni 2001; Bathelt, Malmberg, and Maskell 2004; Asheim and Gertler 2005; Boschma 2005; Ponds, Oort, and Frenken 2009; Fitjar and Rodríguez-Pose 2014; Comunian 2017; Capone, Lazzeretti, and Innocenti 2019). For example, research relationships can be motivated by shared academic interest (Bukvova 2010), but they may also be shaped by commercial and technological dependence, leading to different outcomes for the actors involved (Van Geenhuizen and Nijkamp 2012; Lazonick and Mazzucato 2013). International and inter-cluster research collaboration is especially prevalent in knowledge intensive sectors such as biotechnology and pharmaceuticals (Gertler and Levitte 2005; Leydesdorff and Persson 2010; Ó hUallacháin and Lee 2014; Alkemade et al. 2015). Clusters which are highly connected in global knowledge networks appear to benefit in similar ways to how agglomeration facilitates collaboration and knowledge spillovers in clusters (Boschma 2005). This "relational proximity," like spatial proximity (agglomeration), can be an enabling factor or a barrier to innovation performance (Boschma 2005).

In the context of global knowledge networks, multinational corporations are important for two main reasons: first, they account for a large share of worldwide research investment, and second, they have an ability to connect clusters around the world through their internal global networks. In the United States foreign multinational corporations account for 14-15% of business R&D expenditure, which is around 9% of total R&D expenditure (National Center for Science and Engineering Statistics 2014). Such cross-border research investment is growing (Castellani, Jimenez, and Zanfei 2013; Audretsch, Lehmann, and Wright 2014; Locke and Wellhausen 2014; National Center for Science and Engineering Statistics 2014), including between developed and developing countries (Bruche 2009; Awate, Larsen, and Mudambi 2015). Multinational corporations are uniquely positioned because of their internal global knowledge networks. They tend to have a high level of trust and mutual understanding internally due to the internal mobility of staff, shared goals set out by management, and a common corporate culture, which together facilitate research collaboration between different clusters (Gertler and Wolfe 2006; Nooteboom 2006). This means multinational corporations can form a connecting "pipeline" through which new knowledge can flow between clusters (Bathelt, Malmberg, and Maskell 2004; Morrison, Rabellotti, and Zirulia 2013). The heterogeneity of such knowledge flows can in turn lead to cluster renewal (Njøs, Orre, and Fløysand 2017).

However, there is also evidence that the presence of multinational corporations in a cluster can have a negative effect, because "reverse knowledge flow" can take place. This is especially a concern when an important and highly innovative local firm is acquired (Dunning 2000; Frost 2001; Frost and Zhou 2005; Ambos, Ambos, and Schlegelmilch 2006). Reverse knowledge flow occurs when previously local knowledge spillovers are diverted out of the cluster by a multinational corporation, benefiting their headquarters but not the local cluster. More generally, power imbalances in research collaborations were shown to adversely affect the weaker party (Lazonick and Mazzucato 2013).

While reverse knowledge flows are an area of concern, the potentially negative association between knowledge outflow and cluster innovation performance should be qualified for two reasons. First, multinationals tend to invest in already thriving clusters (De Propris and Driffield 2005; Liu and Buck 2007; Østergaard and Park 2015). The presence of multinationals and the associated knowledge outflow may therefore signal the success of a cluster, rather than any issues concerning reverse knowledge flows. Second, within a multinational corporation, large labs in prominent clusters tend to have significant autonomy over how and what kind of research they conduct (Mudambi and Navarra 2015), which likely mitigates the risks of knowledge outflow to a multinational organization's headquarters. Therefore, reverse knowledge flows, which lower cluster innovation performance, might occur only under specific conditions (Van Geenhuizen and Nijkamp 2012).

Although clusters with remote labs of multinationals might experience knowledge outflow, clusters that host the headquarters of a multinational corporation may benefit from knowledge inflow from branch laboratories in other clusters (Bathelt, Malmberg, and Maskell 2004; Morrison, Rabellotti, and Zirulia 2013; Njøs, Orre, and Fløysand 2017). These clusters might also benefit from their proximity to strategic decision-makers who may favor the multinational corporation's home cluster when making decisions about R&D investment (Sassen and others 2002; Sassen 2008; Belderbos, Leten, and Suzuki 2013; Castellani, Jimenez, and Zanfei 2013). Based on the above considerations, the hypotheses related to knowledge flows are formulated as being positive: a negative effect for knowledge outflow is only expected in rare situations. Like agglomeration, the hypotheses use the term "association," because reverse causalities between knowledge flow and innovation performance are possible: high innovation performance could lead to an increase in knowledge flow, just as knowledge flow can influence innovation performance.

Hypothesis 7: Knowledge inflow has a positive association with cluster innovation performance.

Hypothesis 8: Knowledge outflow has a positive association with cluster innovation performance.

Multinational corporations are just one conduit for the transfer of knowledge over long distances. Other organizations that fulfill this role include universities and local knowledge-intensive firms involved in research collaborations with distant partners (Bathelt, Malmberg, and Maskell 2004; Gertler and Levitte 2005). A prerequisite for research collaboration, whether it is local or taking place over long distances, is relational or cognitive proximity: the extent to which different actors trust each other and share a common set of values (socio/cultural proximity), i.e. the extent to which they "speak the same language." Although social proximity is facilitated by geographical proximity it is not automatic (researchers within the same location may not interact socially). Social proximity can also persist over long geographical distances, for instance between researchers with a similar cultural, educational or career background (Gertler 2003; Ertur and Koch 2011; Fazio and Lavecchia 2013; Nooteboom 2013). Relational proximity is also a concept found in inter-organizational learning theory, which attaches importance to the development of interpersonal relationships, institutional support, and the creation of mutual trust as a prerequisite for successful research collaboration (Dodgson 1992). More broadly, relational proximity can be defined as the capability of clusters (and their organizations and firms) to learn through collaboration with other clusters located at a distance (Camagni and Capello 2002; Cohendet and Amin 2006). Especially diversity in research collaboration relationships at the cluster-level and firm-level are seen as a positive influence on innovation performance (Tödtling and Trippl 2005; Van Beers and Zand 2014). Clusters and organizations that act as brokers between different sub-networks (high degree centrality) appear to benefit greatly from the unique diversity of knowledge available to them (Wasserman and Faust 1994; Beaudry and Breschi 2003; Salman and Saives 2005; Gilsing et al. 2008; Kauffeld-Monz and Fritsch 2013).

Until relatively recently, research collaboration was viewed as purely positive in enhancing innovation in clusters. Particularly in high-tech sectors, research collaboration through long-distance networks has been regarded as crucial for corporate innovation performance, this includes sectors such as biotechnology (Gertler and Levitte 2005; Cooke 2007), automotive technology (Lorentzen and Gastrow 2012), electronics (Ernst 2009), and aerospace (Frenken 2000). However, several newer theoretical perspectives have qualified this positive view on research collaboration. Notable are concerns over the potential for external/international collaborations to divert resources away from internal/domestic collaborations, and that specific positions within the collaboration network structure are more favorable than others. Empirical evidence shows that in some cases international/external research collaboration has been found to weaken local research activity and interaction (Leydesdorff and Sun 2009; Kwon et al. 2012; Van Geenhuizen and Nijkamp 2012; Ye, Yu, and Leydesdorff 2013). While this re-orientation from national to international collaboration relationships is not necessarily harmful, high rates of international network participation, for instance through R&D investment by multinational corporations in clusters that lack the capacity to absorb its benefit, may lower the overall innovation performance of clusters and the organizations located within them (De Propris and Driffield 2005; Fu 2008; Chang, Chen, and McAleer 2013; Ebersberger and Herstad 2013; Hottenrott and Lopes-Bento 2014).

Similar to agglomeration and knowledge flows, inter-cluster collaboration networks can have both a positive and negative association with cluster innovation performance. Network reach (simple degree centrality) is generally perceived to be positive because network reach increases a cluster's access to new sources of knowledge. However, maintaining a relatively large network (high network density; weighted degree centrality) requires clusters of sufficient size and absorptive capacity in order to benefit from the knowledge spillovers and learning that can arise from long-distance research collaborations (Boschma 2005; Fu 2008; Lau and Lo 2015; Tomás-Miquel, Molina-Morales, and Expósito-Langa 2019). Hypothesis 9 and 10 both assume a positive association between the reach and density of the knowledge network and cluster innovation performance, although a lack of association is possible in situations where technology clusters lack sufficient absorptive capacity.

Hypothesis 9: The reach of the inter-cluster collaboration network has a positive association with cluster innovation performance.

Hypothesis 10: The density of the inter-cluster collaboration network has a positive association with cluster innovation performance.

2.4.4 Path Dependence

Path dependence occurs when the current status, or future development of a firm, industry sector, technology cluster, or city region depends on factors (knowledge, experience, institutions, resources, networks, etc.) that were acquired or accumulated in the past (Simmie and Strambach 2006; Martin and Simmie 2008). Path dependence can be seen as the intermediate development phase between the path creation and path breaking phases (Martin and Simmie 2008). Path dependence mirrors the stages of the industry sector life cycle, which consist of growth (path creating), mature (path dependent), and decline phases (path breaking) (Martin and Sunley 2011; Neffke et al. 2011). During the emerging phase an industry sector or cluster produces radically new products and technologies. During the mature phase, the industry sector or cluster produces more optimization-focused innovations (Audretsch and Feldman 1996a; Martin and Sunley 2003; Tidd, Bessant, and Pavitt 2005). During this phase the local accumulation of skills, knowledge, and innovation capabilities can create a virtuous cycle of innovation that gives the cluster a sustainable competitive advantage which enables a technology cluster to thrive and experience strong innovation performance for an extended period of time (Porter 1998, 2000).

However, path dependence need not always be positive: negative path dependence is also possible, a situation in which a cluster becomes locked into old industry sectors, fails to invest in new technologies, and this results in a gradual or sometimes rapid decline in the available innovation capacity of the cluster (Elbaum and Lazonick 1984; Tödtling and Trippl 2005; Maskell and Malmberg 2007; Martin and Simmie 2008; Vaan, Frenken, and Boschma 2019). Such a trajectory may be part of a technological or economic shift, causing path breaking, but may also be due to, or be accelerated by, the departure of key firms or institutions from a cluster (Martin and Simmie 2008; Suire and Vicente 2009; Østergaard and Park 2015). However, a strong technology cluster can persist even as technologies change, and successful clusters transition from old technologies to newly emerging ones (Crescenzi and Rodríguez-Pose 2011; Martin and Sunley 2011; Crescenzi and Jaax 2017). Such a transition is not automatic, because existing institutional configurations and networks may need to be reformed (Vaan, Frenken, and Boschma 2019). New technology path creation often requires coordination of multiple actors within a cluster and not just a shift by a single firm (Steen and Hansen 2018). Therefore, the following hypothesis applies to growing or mature industries, where the accumulation of skills and experience confer benefits to the cluster.

Hypothesis 11: Past cluster innovation performance has a positive influence on current cluster innovation performance.

The sustainable energy technology sector is seen as an emerging sector and can therefore be characterized as a path creating sector (Steen and Hansen 2018), especially due to its role in socio-technological transitions (Geels et al. 2017). For this reason the influence of path dependence in the sustainable energy technology sector is likely to be weaker than in other sectors. Although the health technology sector is also part of socio-technological transitions, it is seen as a more mature and established high technology sector. This difference is formulated in hypothesis 12.

Hypothesis 12: The health technology sector has stronger path dependence compared to the sustainable energy technology sector.

2.5 Summary

The 12 hypotheses formulated in this chapter address the three main knowledge gaps highlighted in the introduction chapter: (i) the global spatial distribution of sustainability technology clusters and their knowledge networks, (ii) the association between cluster innovation performance and cluster characteristics, and (iii) sectoral differences, specifically concerning the role of socio-technological transitions. These knowledge gaps have arisen because of a lack of research and innovation-related data about the sustainability technology sectors that is global in scope, yet at the spatial scale of technology clusters.

With regard to the first knowledge gap, two hypotheses are formulated (hypotheses 1 and 2). Hypothesis 1 posits a shift to Asia in terms of the creation and growth of sustainability technology clusters. Hypothesis 2 suggests that the emerging sustainable energy technology sector has a less dense knowledge network and less agglomeration. No other hypotheses are formulated due to a lack of theory.

The second knowledge gap, innovation performance, is addressed by ten hypotheses, which are grouped based on four types of cluster conditions: agglomeration (hypotheses 3-5), national innovation system (hypothesis 6), knowledge network (hypothesis 7-10), and path dependence (hypotheses 11 and 12). The larger number of hypotheses is reflective of the rich literature on innovation performance, but it also highlights the extent of the theoretical ambiguity that still exists (Crescenzi et al. 2019).

The third knowledge gap, sectoral differences, is addressed by two hypotheses (hypotheses 2 and 12). Research about the influence of sectoral differences on the spatial distribution and innovation performance of technology clusters is mainly explorative in nature. While it is obvious that sectors are different (Binz et al. 2017), and their development phase and knowledge base are important points of difference (Ter Wal and Boschma 2011; Carlsson 2013), there is limited theory to guide expectations of *how* sectoral differences influence cluster innovation performance, especially when considering the role of socio-technological transitions.

Hypotheses 1 and 3-11 are evaluated separately for the health technology and sustainable energy technology sectors in chapter 5 and 6. Chapter 7 addresses all hypotheses in a broad sectoral comparison of health technology and sustainable energy technology within the context of other high technology sectors. The next two chapters (chapter 3 and 4) describe the data and methodology used to empirically evaluate the hypotheses proposed here.

2.6 Selected Terminology

Some of the terminology used in this dissertation may differ from uses in other research, hence the need for a list of selected terminology. The list serves as a reference for readers who do not have the time to read this chapter and chapters 3 and 4 in detail, but who are reading later chapters of the dissertation.

Agglomeration The spatial concentration of similar or related economic activity and actors in a particular location (Kobayashi 2019)

Sectoral innovation system A set of products or services and related actors connected through market and non-market interactions aimed at the creation, production, and sale of the products or services (Breschi and Malerba 1997).

Innovation performance The generation of new knowledge, or combination of existing knowledge in new ways, and its application in an economically useful way (Schumpeter 1934; Drucker 1985; Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005).

Knowledge base (sectoral) The type of knowledge which technological innovation in a particular sector is based on, for example: basic scientific research or engineering and design (Stankiewicz 2002; Carlsson 2013).

Knowledge network A set of relationships between individuals and/or organizations through which knowledge is exchanged and/or co-created, which can exist within close spatial proximity but also at (very large) distances (Boschma 2005; Bukvova 2010).

Knowledge network density The frequency with which an entity (for example, an individual, organization or cluster) maintains knowledge-based relationships with other such entities; also referred to as the weighted degree centrality in social network analysis theory (Wasserman and Faust 1994).

Knowledge network reach The number of other entities (for example, individuals, organizations or clusters) that a particular entity is connected to through a knowledge-based relationship; also referred to as simple degree centrality in social network analysis theory (Wasserman and Faust 1994).

National innovation system The flow of technology and information among people, enterprises, universities and government research institutions, as well as the entrepreneurial culture, and laws and regulations of a country related to innovation, which together determine its national innovation performance (Lundvall 1992; Nelson and Rosenberg 1993; De Rassenfosse and Potterie 2009; Autio et al. 2014).

Path dependence (of innovation performance) A situation whereby future innovation performance is shaped by past innovation performance, which also caused the accumulation of skills, knowledge resources, experience, reputation, relationships, etc. (Martin and Simmie 2008)

Patent assignee The person or organization which is assigned ownership of the patent (Breitzman and Mogee 2002).

Patent citation A mention or reference to a patent in another patent document which describes similar technological content, made by a patent inventor or patent examiner (Breitzman and Mogee 2002).

Patent inventor The author of the knowledge disclosed in a patent and who is designated as an inventor in the patent application documents (Breitzman and Mogee 2002).

Regional innovation system The flow of technology and information among people, enterprises, universities, and government research institutions in a region related to innovation, which together determine regional innovation performance (Cooke, Heidenreich, and Braczyk 2004; Cooke 2007).

Regional specialization The level of agglomeration of a particular industry or technology sector in a region, relative to the total economic output (or innovation output) of that region (Tabuchi and Thisse 2006).

Technology Cluster A spatial concentration of innovation activity related to a particular industry or technology sector (Nooteboom 2006; Casper 2013).

Chapter 3

Data and Methodology

3.1 Introduction

This chapter provides a detailed description of the cluster innovation performance model and a brief overview of the data and methodology used for cluster identification. The cluster identification methodology builds on earlier research (Catini et al. 2015; Alcácer and Zhao 2016). Likewise, the innovation performance model is based on earlier knowledge production functions (Ó hUallacháin and Leslie 2007; Charlot, Crescenzi, and Musolesi 2014). Both incorporate some notable improvements. The new cluster identification methodology uses a "heat map" spatial interpolation technique (kernel density estimation, see Rosenblatt (1956) and Parzen (1962)), which is widely used in other fields, but had not previously been applied in technology cluster studies. The new methodology not only identifies clusters but also measures their size, knowledge networks, innovation performance, and other cluster characteristics. This requires the careful selection and correction of data. For this reason a single source of patent data is used in this study (namely the patent grant database of the United States Patent and Trademark Office) and a home bias correction factor is applied (Bacchiocchi and Montobbio 2010). More precise identification of technology clusters enables more precise measurement of cluster indicators and the construction of a unique global database of technology cluster metrics.

The technology cluster indicators are subsequently used in the cluster innovation performance model, which differs considerably from other knowledge production functions (Charlot, Crescenzi, and Musolesi 2014; Crescenzi and Jaax 2017). Knowledge production functions were used to analyze the relationship between knowledge inputs (e.g. researchers) and knowledge outputs (e.g. patents). The new cluster innovation performance model takes a different approach, viewing knowledge output *relative to* knowledge input, and thus defining innovation performance as a productivity measure. The model measures the innovation out-performance of a cluster relative to the available knowledge inputs. By removing knowledge inputs as an independent variable, the correlations of other variables becomes more visible (e.g. knowledge networks). The model also uses patent citations instead of patent counts. Patent citations are proxies for the quantity and *value* of innovation (Hall, Jaffe, and Trajtenberg 2005). The combination of a new cluster identification methodology with a new cluster innovation performance model provides a fresh empirical perspective on technology clusters worldwide, including in sustainability technology sectors.

This chapter is the first of two methodology-related chapters. This chapter begins with a short review of notable scientometric studies, highlighting different types of scientometric data and relevant research applications (section 3.2). The review is followed by a concise explanation of the data and cluster identification methodology (section 3.3). An in-depth discussion of the methodology is presented in the next chapter (chapter 4). The identification of high technology sectors, including health technology and sustainable energy technology, are discussed in section 3.4. Section 3.5 provides an overview of the cluster indicators, which measure innovation performance, and different aspects of cluster agglomeration and knowledge networks. This is followed by a description of the cluster innovation performance model in section 3.6, which includes the model development process, implementation, and the selection of time periods. The chapter concludes with a summary and discussion of the new cluster innovation performance model (section 3.7).

3.2 Scientometric Data and Selected Applications

Scientometric data are the "paper trail" of innovation activity (Jaffe, Trajtenberg, and Henderson 1993, 3) and they has been widely applied in innovation studies since the 1990s. This section provides a survey of the main sources of scientometric data and lists some of applications relevant for the cluster innovation performance model indicators which are described in section 3.5. Table 3.1 lists seven applications of scientometric data together with relevant references to scientific articles published in respected journals such as *Research Policy*, *Journal of Economic Geography*, and *Scientometrics*. The references are not exhaustive but include at least one early example of an application and one relatively recent example of an application. The scientometric methods discussed are patent counts and growth rates, citation rates, authorship and co-authorship analysis, trans-national corporate R&D networks, and cluster identification.

The use of patent counts as a proxy for inventive activity is one of the simplest applications of scientometric data and they are widely used in innovation studies (Acs, Anselin, and Varga 2002; Ó hUallacháin and Leslie 2007; De Rassenfosse and Potterie 2009; Charlot, Crescenzi, and Musolesi 2014; Crescenzi and Jaax 2017). Despite their popularity there are concerns about using patent counts because of the large variations in patenting propensity, which can cause distortions. Arundel and Kabla (1998) and others have noted large differences in patenting propensity between industry sectors (Kleinknecht, Van Montfort, and Brouwer 2002; Hall, Jaffe, and Trajtenberg 2005). Yang and Kuo (2008) and others have also noted significant differences in patenting propensity between countries due to economic and governance factors (De Rassenfosse and Potterie 2009; Bacchiocchi and Montobbio 2010). These concerns are addressed by exercising caution when making inter-sectoral or inter-country comparisons. They are also less of a concern when trying to observe trends, such as the growth of patent output in a particular sector or country Boeing, Mueller, and Sandner (2016).

Although patent counts are used as a measure of *quantity*, the *quality* of scientific output is often measured using citation frequencies. Citation frequencies provide insight into the value and importance of patents and scientific publications (Nagaoka, Motohashi, and Goto 2010; Bukvova 2011; Waltman et al. 2012), andthey were used to measure the innovation or scientific performance of different types of organizations. Joo, Oh, and Lee (2016) use patent citations to show changes in the innovation performance of emerging firms compared to technology leaders in high technology industries. Waltman et al. (2012) use citation frequencies as a measure of the quality of universities. However, as with patent counts, citation propensities also vary by sector and country (Bacchiocchi and Montobbio 2010).

Patents and scientific publications also contain authorship (inventor) information, which may include affiliated organization (universities, industry, government) and geographic location of authors, providing insight into the organizations and places where innovation is taking place. These insights also allow co-authorship to be explored, including between individuals, organizations, organization types (e.g. between university and industry), andlocations (e.g. international or inter-regional collaboration). Co-authorship is generally considered to be a proxy for research collaboration (Wasserman and Faust 1994; Bukvova 2010), although some co-authorship awards are made for honorary or organizational-political reasons and do not represent the real intellectual contribution of a co-author (Bukvova 2010). The situation is different in the case of patent *ownership* ('assignment') where real economic interests are at stake because owners are entitled to royalties from the exploitation of a patent. The patent owner is often the funder of the research, which may have taken place at another organization, such as a university. Depending on the intellectual property policies in place, a patent invented at a university could be assigned to the university, to individual researchers, to a funding organization such as a high technology company or to a combination of co-assignees (Gautam, Kodama, and Enomoto 2014). Despite the potential inaccuracies of using co-authorship or co-assignee data as a proxy for research collaboration, co-authorship and co-assignee data are widely used in scientometric studies, especially when exploring research collaborations at larger aggregate scales, such as between cities or countries (Ó hUallacháin and Lee 2014; Alkemade et al. 2015), where the measurement uncertainties of co-authorship are less likely to influence the results (Wagner and Leydesdorff 2005; Leydesdorff et al. 2013).

The geographic information from scientometric publications can also be used to identify spatial concentrations of knowledge output, i.e. to identify clusters in patent-rich sectors such as semiconductors, photovoltaics, and biomedical technology (Duranton and Overman 2005; Leydesdorff et al. 2014; Catini et al. 2015; Alcácer and Zhao 2016) or to identify top innovation cities worldwide (Bergquist, Fink, and Raffo 2017). Some exploratory studies have combined the identification of clusters with the study of inter-cluster knowledge networks (Leydesdorff et al. 2014; Ó hUallacháin and Lee 2014) and cluster size (Bergquist, Fink, and Raffo 2017), although these studies do not address the aforementioned measurement issues related to patenting propensities and co-authorship. The literature related to cluster identification is addressed in more detail in chapter 4.

This brief survey of scientometric studies (table 3.1) shows that the most common sources of scientometric data are (i) patent databases such as those maintained by the United States Patent and Trademark Office and European Patent Office, and (ii) scientific publication abstract databases such as *Scopus* and *Web of Science*, which are owned and maintained by publishing companies. For national studies it is not uncommon for other national patent databases to be used, such as the Japan Patent Office database (Gautam, Kodama, and Enomoto 2014) or China's State Intellectual Property Office database (Boeing, Mueller, and Sandner 2016).

Table 3.1: Overview of scientometric data applications and selected literature relevant to this dissertation.

Data	**Application**	**Selected References**
Patent	Patent count as proxy for innovation activity	Acs, Audretsch, and Feldman (1994), Acs, Anselin, and Varga (2002), Ó hUallacháin and Leslie (2007) De Rassenfosse and Potterie (2009), Charlot, Crescenzi, and Musolesi (2014)
Patent	Growth rate as proxy for innovation performance	Crescenzi, Rodriguez-Pose, and Storper (2007), Boeing, Mueller, and Sandner (2016)
Patent and Scientific Publication	Citation rate as proxy for innovation performance	Mancusi (2008), Waltman et al. (2012), Joo, Oh, and Lee (2016), Kwon, Lee, and Lee (2017)
Patent	Identifying actors involved in innovation	Meyer, Siniläinen, and Utecht (2003), Bhattacharya (2004), Park, Hong, and Leydesdorff (2005)
Patent and Scientific Publication	Research collaboration networks	Kwon et al. (2012), Leydesdorff et al. (2014), Zheng and Kammen (2014)
Patent	Trans-national corporate R&D investment	Bhattacharya (2004), Belderbos, Leten, and Suzuki (2013)
Patent	High-technology cluster identification method	Duranton and Overman (2005), Leydesdorff et al. (2014), Catini et al. (2015), Alcácer and Zhao (2016), Bergquist, Fink, and Raffo (2017)

3.3 Technology Cluster Identification Method

This section provides a brief summary of the 4-step “heat map” technology cluster identification method used in this study. A detailed description of the relevant literature, design criteria and comparisons with earlier studies are provided in chapter 4. The aim of the new “heat map” method is (i) to identify technology clusters on a global scale based on real inventive activity, following the so-called “organic” cluster approach put forward by Duranton and Overman (2005) and Alcácer and Zhao (2016), (ii) to take advantage of the Kernel Density Estimation (KDE) or “heat map” approach to identifying high concentrations of inventive activity, because although KDE is a common spatial analysis tool in various disciplines (Bithell 1990; Baxter, Beardah, and Wright 1997; Anderson 2009), it appears to not have been previously applied to innovation activity or patents, (iii) to improve on the performance, in terms of accuracy, of cluster identification compared to pre-existing boundary or organic boundary cluster identification methods, as measured using the benchmarking criteria proposed by Alcácer and Zhao (2016).

The cluster identification method applied in this study consists of 4 main steps, each of which is briefly described in the relevant subsection. Table 3.2 provides an overview of the steps and notable challenges and decisions to be made. The method begins with data selection (step 1) and geocoding (step 2). This is followed by a weighting calculation and home bias correction (step 3) and clustering algorithm parameter calibration (step 4).

Table 3.2: Steps and challenges of the technology cluster identification method (this study).

Step	Description and Challenges
1	*Data Selection*: Choice of USPTO patent database.
2	*Geocoding*: Process to optimize accuracy and efficiency of converting addresses to coordinates.
3	*Weighting and Home Bias Correction*: Calculating a correction factor to compensate for the United States-bias caused by using USPTO patents.
4	*Clustering Parameters*: Calibration to identifying suitable parameters that meet cluster identification goals.

Step 1: Data Selection

Step 1 involves choosing the patent database to be used. Patent databases contain patents from different countries, provide a significant level of detail about the technologies involved, cover long time series, and contain information about the inventors and patent owners (Schmoch 1999; Acs, Anselin, and Varga 2002). This means that patents can provide a large amount of information about research and innovation at a temporal and spatial scale unmatched by other data sources. Patent data can also be used for a range of useful applications, as shown earlier in table 3.1. However, challenges arise when deciding which patent database to choose (or whether to use multiple patent databases) and how to address the home bias effect (Yang and Kuo 2008; Bacchiocchi and Montobbio 2010).

In this study patent data are obtained from the PatentsView database which is published by the Office of Chief Economist in the United States Patent and Trademark Office (USPTO) and contains data on 6,647,699 patent grants from the USPTO (May 2018 edition). Because of the delay between patent application and grant, the most recent year for which full patent grant data are available is 2011 (as at time of writing). As the United States are a large and open economy, many foreign entities also apply for patent protection at the USPTO, and therefore the PatentsView database provides the most extensive global coverage of patents among national patent databases and the European Patent Office (Kim and Lee 2015). The choice of a single patent database means that some form of home bias adjustment needs to be made. On the other hand, the advantage of using a single source of patents means that all patents are granted in accordance to a single standard, improving the validity of making international comparisons (Toivanen and Suominen 2015). Patent data selection is discussed in detail in section 4.4.1 of chapter 4.

Step 2: Geocoding

Step 2 pertains to using the address information of patents to locate where the innovation activity leading to the patent actually took place. Patent inventor location is used to identify R&D activity because it reflects the most likely "true" location of where the R&D was carried out. To identify areas of high R&D activity, inventor address information is converted into coordinates through a geocoding process. For example, the address "Delft, The Netherlands" is converted into the coordinates 51.9995142, 4.2938295. The PatentsView database provides coordinates for patent addresses, but some of these are inaccurate, requiring the re-geocoding of certain addresses. The re-geocoding process is described in detail in section 4.4.2 of chapter 4.

Step 3: Weighting and Home Bias Correction

Step 3 concerns the calculation of a location weighting and home bias correction factor. After geolocating inventor addresses, each identified location receives a weighting to reflect the number of inventions produced there. This weighting is calculated by summing the number of patent inventors with an address in a location, with some adjustment made for the number of inventors per patent (fractional counting).

A home bias correction is also carried out. As mentioned earlier, the home bias effect manifests itself in national patenting frequencies (relative to R&D activity) and a citation bias, whereby local patents are cited more frequently (De Rassenfosse and Potterie 2009; Bacchiocchi and Montobbio 2010). In addition to these biases, the patenting frequency of an inventing country at a foreign country's patent office can also be influenced by economic and technological factors such as the volume of its R&D activity, the sectoral composition of its economy, export dependence, its primary export markets and its level of technological advancement (Yang and Kuo 2008). To quantify a home bias effect, with a view of performing some kind of correction, the home economy's patenting and citation frequencies need to be compared with a "similar" economy. The USPTO is the national patent office of the United States, a highly advanced economy with innovation taking place at the technological frontier. In this context Japan is a logical comparison country because its qualitative patenting profile is the most similar to the United States compared to other countries, and this has been the case for an extended period of time (Mancusi 2008; Toivanen and Suominen 2015). The calculations of the weightings and the home bias correction factor based on comparing the United States and Japan, are described in detail in section 4.4.3 of chapter 4.

Step 4: Clustering Parameters for Heat Map Algorithm

Step 4 encompasses the implementation of a heat map algorithm to calculate the density of patent output. Areas of high patent concentration are subsequently identified as clusters. The heat map method offers some potential advantages over the "organic" cluster identification methods used in earlier studies. Alcácer and Zhao (2016) assigned patent addresses to particular cities and then combined cities in close proximity (less than 40 mi or 64.4 km) into the same cluster. The KDE method however skips the need to assign an address to a city as the weightings of nearby locations are combined. This means that addresses of neighborhoods, neighboring cities, adjacent villages or a university campus are automatically interpolated into one "hot spot" (cluster). The KDE method is also less rigid than a fixed 64.4 km boundary as an interpolation method is used instead. The cluster identification technique used by Bergquist, Fink, and Raffo (2017), density-based spatial clustering of applications with noise (DBSCAN), is similar to KDE in the sense that it is a density-based algorithm.[1] Catini et al. (2015) identifies clusters based on networks of institutions. This network-based cluster identification approach probably works better for scientific publications in the medical sciences in which co-authorship between multiple organizations is highly prevalent, compared to other sectors.

[1] It is interesting to note that DBSCAN is also implemented in QGIS, the software used for KDE in this study. A comparison between DBSCAN and KDE could be performed in future.

When applying KDE to identify clusters, decisions must be made about two important variables: the interpolation range (R) at which patent inventors are likely to be part of the same cluster, and the concentration threshold (T), for recognizing an area as being of "high concentration" and thus part of a technology cluster. The interpolation range can be decided based on several criteria, for example Van Egeraat et al. (2018) uses commuting distance while Alcácer and Zhao (2016) uses 20 mi (32 km, without any justification given). Acs, Anselin, and Varga (2002) notes that within a 50 mi (80.5 km) distance from the boundaries of a metropolitan statistical area, there is still some positive innovation effect. The distance cited by Acs, Anselin, and Varga (2002) is about four times the largest average daily commuting distance of a US city (Atlanta, GA, average commuting distance of 20.6 km) (Kneebone and Holmes 2015). This diversity in approaches gives no clear guidance about the "correct" interpolation range. A sensitivity analysis is therefore undertaken to identify an optimum interpolation distance between 15 and 50 km. There is also no guidance in the literature about which concentration threshold: the concentration of patenting activity should be among the upper percentiles of global R&D activity, however determining where to set this threshold is subjective. Should it be at the 90$^{\text{th}}$, 95$^{\text{th}}$ or 97.5$^{\text{th}}$ or at an even higher percentile threshold? Sensitivity analysis is also used to determine a suitable concentration threshold.

The optimum values of the interpolation distance (R) and threshold concentration (T) are subject to three conditions or goals: a maximum cluster size (A_{max}), the ability of the algorithm to correctly identify patents within the same cluster (D_{same}) or a different cluster (D_{dif}), and the number of clusters (n). The maximum cluster size is imposed to avoid identifying unrealistically large clusters which likely lack internal coherence. Correctly identifying clusters as belonging to, or not belonging to, a cluster is used as a measure of the clustering algorithm's performance. Identifying a large number of clusters shows that the algorithm is able to identify relatively small clusters. Based on these conditions, the calibrated heat map algorithm, which is applied in this study, has an interpolation range value of $R = 25$ km and a concentration threshold value of $T = 97.5\%$. Based on the cluster identification performance measure proposed by Alcácer and Zhao (2016), the heat map method used in this study appears to out-perform pre-set boundary cluster identification methodologies and the best-performing organic clustering method. For the calibrated heat map algorithm $D_{same} = 99\%$ and $D_{dif} = 66\%$. For the organic clustering method by Alcácer and Zhao (2016) $D_{same} = 100\%$ and $D_{dif} = 59\%$. However, it must be noted that the datasets for the present study and Alcácer and Zhao (2016) differ. A detailed description of the parameter calibration exercise and a more detailed comparison between different sectors is presented in section 4.5 of chapter 4.

3.4 Sector Selection

The two sustainability technology sectors, health technology and sustainable energy technology, are the focus of this dissertation. The sectors are part of a socio-technological transition towards a more sustainable healthcare and energy system, which makes the sustainability technology sectors different from "normal" high technology sectors. Sustainability transitions involve not just technological innovations but also social, economic, and regulatory change (Geels 2012). This difference is especially pronounced in emerging and highly innovative sectors rather than in more mature health and sustainable energy technologies such as hydroelectric power or traditional pharmaceuticals (PwC Health Research Institute 2013; OECD 2017). An overview of the sustainability and reference high technology sectors, and their sub-sectors, is given in table 3.3.

Medical life sciences and medical devices are seen as the main sources of health technology innovation (PwC Health Research Institute 2013; OECD 2017), and hence these two sub-sectors are included under the health technology sector. The knowledge base of the medical life sciences sector can be characterized as science-based, while medical devices can be characterized as an engineering and design-based sector, which suggests that there are notable differences in their innovation process (Stankiewicz 2002; Asheim and Coenen 2005; Binz and Truffer 2017). Although the two sectors are considered to be highly innovative, they are relatively mature sectors, with the medical life sciences industry having gained prominence in the United States since the 1980s (Booth 2016). Although the sub-sectors are different from a technological perspective, innovation in both sectors is expected to contribute towards a sustainability transition in the healthcare sector (OECD 2017).

By comparison the sustainable energy sector is in a relatively early development stage and multiple technologies are seen as being highly innovative (CPC Implementation Group 2017; International Energy Agency (IEA) 2019d).In the area of electricity generation, photovoltaics, and wind turbines only reached cost competitiveness with competing energy generation technologies in the late 2010s (International Energy Agency (IEA) 2019d). These technologies no account for about 80% of newly installed renewable energy capacity globally (International Energy Agency 2016; International Energy Agency (IEA) 2019d). Other highly innovative sustainable energy technologies are mainly related to sustainable mobility solutions and include advanced biofuels, electric vehicles, electricity storage (batteries), fuel cells, and hydrogen technology (CPC Implementation Group 2017; International Energy Agency (IEA) 2019d). Among these sectors electric vehicles and wind turbines are seen as engineering and design-based sectors, while the other sectors have a scientific knowledge base (Tidd 2001; Binz and Truffer 2017). The larget number of sustainable energy technology sub-sectors is indicative of the sector's technological diversity. Although it is possible to aggregate sustainable electricity generation and mobility technologies, the professional literature clearly distinguishes between different sub-sectors due to the differences in the technologies involved (International Energy Agency 2016; International Energy Agency (IEA) 2019d). At the same time, these sectors are all seen to be playing a part in a broad-based sustainability transition towards a low or zero-carbon energy system (International Energy Agency (IEA) 2019d)

The reference high technology sectors are selected to provide an aggregate picture of "normal" high technology sectors to provide a benchmark (or reference point) against which to compare the sustainability technology sectors. The reference high technology sectors include eight mature R&D intensive sectors defined by the OECD (Galindo-Rueda and Verger 2016) and two advanced but generic technology sectors, biotechnology and nanotechnology, which are widely application across different industries (OECD 2013). Like the sustainability technology sectors the reference high technology sector has a diverse knowledge base. Aerospace, defense, electrical equipment, machinery and equipment, and motor vehicles are considered to be sectors with an engineering and design knowledge base while the other sectors can be characterized as science-based (Tidd 2001; Binz and Truffer 2017).

In practical terms patents belonging to a particular sub-sector are identified based on the Cooperative Patent Classification system (CPC Implementation Group 2017) and the International Standard Industry Classification (Lybbert and Zolas 2014). This process, and the related classification codes, are described in detail in section 4.4.4 of chapter 4.

Table 3.3: Sectors and sub-sectors of this study.

Health Technology	Sustainable Energy	Reference High Technology
Medical devices*	Biofuels	Aerospace*
Medical life sciences	Electric vehicles*	Biotechnology
	Electricity storage	Chemicals
	Fuel cells	Electronics
	Hydrogen technology	Defense*
	Photovoltaics	Electrical equipment*
	Wind Turbines*	Machinery and equipment*
		Motor vehicles*
		Nanotechnology
		Pharmaceuticals

Note: * marks sectors with an engineering and design knowledge base

3.5 Operationalization and Measurement of Cluster Characteristics

In this section cluster indicators are defined and operationalized. The cluster indicators are proxies of the cluster characteristics used in the descriptive analysis and the cluster innovation performance model. The descriptive analysis involves the spatial distribution of clusters, cluster size, and inter-cluster knowledge networks (hypotheses 1 and 2, subsection 3.5.2 and 3.5.4). The cluster innovation performance model uses an innovation performance indicator as its dependent variable (subsection 3.5.1). The independent variables of the model describe the agglomeration (hypotheses 3-5 , subsection 3.5.2), national innovation system (hypothesis 6, subsection 3.5.3), inter-cluster knowledge network (hypotheses 7-10, subsection 3.5.4), and path dependence characteristics of technology clusters (hypotheses 11 and 12, subsection 3.5.5).

Each subsection describes a different indicator type and begins with some background information about the indicator(s) in question. This is followed by a summary table listing the name, unit, and measurement definition of the indicators for each subsection. Note that a robustness analysis of all the cluster indicators is carried out to determine the appropriate minimum cluster size (see appendix C.1, tables C.1 and C.2). The robustness check shows that a minimum cluster size of ten inventors is appropriate because the smaller cluster size has a negligible influence on averaged indicator values.

3.5.1 Cluster Innovation Performance (Dependent Variable)

The dependent variable of the cluster innovation performance model differs from the dependent variables of earlier knowledge production function studies in two important ways: it uses patent citations instead of patent counts to measure innovation performance and it is a productivity indicator instead of an output indicator (Ó hUallacháin and Leslie 2007; De Rassenfosse and Potterie 2009; Charlot, Crescenzi, and Musolesi 2014). Patent citations are primarily seen as an indicator of patent value and quality (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004; Squicciarini, Dernis, and Criscuolo 2013). Patent citations are generated when another patent refers to a prior patent, an act that can have commercial consequences because the holder of the cited patent may be entitled to certain rights or licensing fees when the citing patent is used (Hall, Jaffe, and Trajtenberg 2005). Whereas the majority of patents are never cited and have negligible economic value, the most economically valuable patents are also among the most frequently cited patents (Hall, Jaffe, and Trajtenberg 2005; Yang, Qian-nan, and Ze-yuan 2008). Patent citations can therefore be seen as a suitable proxy for innovation output because they signal a patent's economic value, which is central to the definition of innovation: the application of knowledge in an economically useful way (Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005).

Formulating innovation performance as a productivity indicator instead of an output indicator has another important advantage: it more clearly reveals the association between cluster innovation performance and different cluster characteristics such as agglomeration, knowledge networks, and path dependence. When knowledge output is used as the dependent variable (as measured by patents or patent citations) there is usually a high correlation knowledge inputs (such as researchers) which are often the dominant independent variable in a knowledge production functions (Hagedoorn and Cloodt 2003; Charlot, Crescenzi, and Musolesi 2014). The step of dividing innovation output by input, and thus creating a productivity indicator isolates the innovation out-performance of a technology cluster relative to the available inputs, allowing the influence of cluster characteristics on innovation performance to be analyzed more precisely.

The innovation performance of a technology cluster (IVP, table 3.4) is measured by dividing the number of patent citations (CIT, proxy for innovation output) by the number of inventors (INV, proxy for innovation input). The number of inventors (INV) is calculated based on a count of unique inventor names (first name and last name) with addresses in the cluster. A single inventor can produce multiple patents and therefore the number of inventors serves as a proxy for the number of researchers in the cluster. The number of researchers is a frequently used input variable in knowledge production functions (Hagedoorn and Cloodt 2003; Ó hUallacháin and Leslie 2007).

A further advantage of using patent citations in the dependent variable is that it makes the innovation performance indicator less sensitive towards quantitative patenting strategies and litigation-focused patenting. When pursuing a quantity-based patenting strategy an inventor might disclose knowledge in a large number of lower quality patents (which receive few citations) instead of filing a small number of high quality patents (which receive many citations). Quantitative patenting targets are used in China and other countries where institutions receive funding based on the number of patents filed (Boeing, Mueller, and Sandner 2016). Another concern is that patents are filed for the sake of blocking innovations or for potential future litigation (Meurer 2016). This means that patent counts can be inflated in ways that do not reflect the underlying innovation activity. Patent citations measure patent value and therefore they are less influenced by a quantitative patenting strategy or by the filing of “frivolous” (and low-quality) patents for the purposes of future litigation.

Table 3.4: Cluster innovation performance indicator.

Dependent Variable	Unit	Measurement Definition
Innovation Performance, IVP	Citations per Inventor	$IVP = CIT/INV$, where CIT is the number of citations received by cluster patents (inventor weighted) and INV is the number of unique inventor names with addresses inside the cluster.[2]

3.5.2 Cluster Agglomeration Characteristics

The agglomeration characteristics of clusters appear to have a close association with cluster innovation performance. As noted in chapter 2, agglomeration is typically approached from two theoretical perspectives: a quantitative scale-based perspective (Marshall 1920) and a qualitative perspective, whereby agglomeration depends on the presence of different types of innovation actors (universities, firms, public research institutions, venture capital, etc.), and the relationships between them (Jacobs 1969; Acs, Audretsch, and Feldman 1994; McCann 2008). Agglomeration effects can occur on different spatial scales, from a very local level (distance of a few km) to a broader regional level (distance of around 50-200 km) (Anselin, Florax, and Rey 2013). Four agglomeration indicators are included in the cluster innovation performance model and they measure the underlying concepts that are part of hypotheses 3-5. The indicators are cluster size and adjacency, both scale-based agglomeration indicators (hypothesis 3), regional specialization (hypothesis 4), and corporate research (hypothesis 5). An overview of the indicators, their units and measurement definition is provided in table 3.5.

Cluster size (PAT) is a scale-based agglomeration indicator based on the number of patents invented in a cluster. A patent correction factor (COR_{PAT}) is applied to compensate for the home bias effect. Patents with multiple inventors in different clusters are allocated proportionally to each cluster.

Adjacency (ADJ) is a proximity indicator (Anselin, Florax, and Rey 2013) which measures the influence of other nearby clusters. The indicator is a proxy for the neighborhood effect and is calculated by adding the total number of patents from all other clusters located within 200 km from the center of the cluster.[3] The choice of 200 km as a maximum distance from the center of the cluster is based on a sensitivity analysis which show that 400 km or 800 km distances lack a statistically significant influence on the dependent variable. Sensitivity analysis is a commonly used and accepted method to identify the cut-off distance for linear proximity indicator (Anselin, Florax, and Rey 2013).

Regional specialization (SPE) is a measure of the relative size of the *sectoral* technology cluster compared to the local region (all sectors). A high value of SPE indicates that a particular sectoral cluster accounts for a large share of local research output. A low value suggests that many other sectors are also present in the local region. Low values are more likely to occur in urban areas

[3]The choice of 200 km from the center of the cluster fits with the observation by Acs, Anselin, and Varga (2002) who observe research spillovers at 80.5 km (50 mi) beyond the borders of a metropolitan statistical area but not at 120.7 km (75 mi). If it is assumed that a metropolitan statistical border is located approximately 100 km from its center, then the two observations validate each other.

which have a large and diversified innovation landscape with multiple high technology industry sectors (Capello 2009).

Corporate research (CRP) is a qualitative agglomeration indicator that measures of the share of cluster patents owned by private-sector actors (as opposed to patents held by universities and government actors). The indicator serves as a proxy of a cluster's absorptive capacity because an actively innovating private sector suggests that firms located in the cluster have the capacity to absorb and benefit from local knowledge spillovers (Capello 2009; Chang, Chen, and McAleer 2013; Qiu, Liu, and Gao 2017).

Table 3.5: Cluster agglomeration indicators.

Agglomeration Indicators	**Unit**	**Measurement Definition**
Cluster size, PAT	Patents	Number of patents invented in the *sectoral* cluster (inventor weighted). For non-US clusters, PAT is multiplied by the patent correction factor (COR_{PAT}).
Adjacency, ADJ	Patents	$ADJ = \sum_{r=0}^{250} PAT_j$ where PAT_j is the total number of same-sector cluster-based patents within a 250 km radius (r) of the centroid/geographic center of the cluster. For non-US clusters, PAT is multiplied by the patent correction factor (COR_{PAT}).
Regional specialization, SPE	Percentage (share of *regional* patents)	$SPE = PAT/TPT$, where TPT is the number of patents invented within the borders of the cluster from *all sectors*. A high value of SPE suggests that a particular sectoral cluster is relatively large as compared to other sectoral clusters located in the region.
Corporate research, CRP	Percentage (share of *sectoral* cluster patents)	$CRP = \frac{PAT - PAT_{UNI} - PAT_{GOV}}{PAT}$ where PAT_{UNI} and PAT_{GOV} are the number of university- and government-held patents, respectively. Government and university-held patents are identified using a word list and the USPTO's assignee classification system (see appendix A.1).

3.5.3 National Innovation System

In addition to local and regional spatial agglomeration, national factors, such as the quality of the national innovation system (hypothesis 6), also influence cluster innovation performance (Nelson and Rosenberg 1993; Palmer et al. 2018). A number of national innovation indexes with international coverage have become available in recent years. In this study the quality of the national innovation system is measured using data from the Global Competitiveness Index, one of the oldest annually updated innovation indexes, which has been published by the Geneva-based World Economic Forum since 2005 (Schwab and Sala-i-Martin 2015). Rather than using the aggregate competitiveness index values, the twelfth pillar (innovation) is used, which is a composite scalar indicator (1-5) that combines equally weighted scores of national private and public sector research investment, the quality of the higher education system, university-industry collaborations, and protection of intellectual property for almost every country in the world (Porter et al. 2008; Schwab and Sala-i-Martin 2015). In this study data from the 2011 Global Competitiveness Report is used, which overlaps with the study period (see section 3.6.4).

Table 3.6: National innovation system indicators.

National Indicator	**Unit**	**Measurement Definition**
National Innovation System Quality, NSQ	None (composite indicator)	National measure of private and public sector research investment, quality of higher education system, university-industry collaborations, and protection of intellectual property.

3.5.4 Inter-Cluster Knowledge Networks

The position of a technology cluster in global inter-cluster knowledge networks is seen as an important factor associated with cluster innovation performance. Hypotheses 7-10 explore inter-cluster knowledge flows and the reach and density of a cluster's knowledge network (Asheim and Gertler 2005; Boschma 2005; Malecki 2014). An overview of the four network indicators is shown in table 3.7.

The first two network indicators explore the "import" and "export" of knowledge from clusters. Knowledge inflow (MNC, the "import" of knowledge) occurs when cluster-based organizations acquire knowledge from outside the cluster. Such a situation arises when a multinational corporation headquartered in one cluster operates a remote lab in another cluster. Although remote labs in foreign countries are a common feature of multinational corporations (Castellani, Jimenez, and Zanfei 2013), public agencies and some universities also have research activities and permanent facilities in multiple countries (Moulin 1992; Healey 2014). Conversely, knowledge outflow (LAB, the "export" of knowledge) occurs when knowledge developed inside the cluster is acquired by an outside organization. Knowledge flows can be identified when the owners of a patent (assignees) and the inventors are located in different clusters. The cluster where the patent was invented "exports" knowledge to the cluster which owns the patent (the "importer"). Restating the aforementioned using the terminology of social network analysis: MNC is the weighted inbound degree centrality of the inter-cluster inventor-assignee network and LAB is the weighted outbound degree centrality of the inter-cluster inventor-assignee network. To account for differences in cluster size, both indicators are divided by the number if inventors (INV) in the cluster (Wasserman and Faust 1994).

The third and fourth network indicators measure the position of a technology cluster within the inter-cluster co-invention network. The co-invention network is derived from patents with inventors located in two or more different clusters. Network reach (NET_S), or simple degree centrality, is a count of the number of different clusters that a cluster is connected to. Network density (NET_W), or the weighted degree centrality, is a measure of the total number of knowledge network links per inventor. While having a diverse network can help a cluster access diverse sources of knowledge, a network too diverse and too dense may also act as a barrier to cluster innovation performance (Boschma 2005)

Table 3.7: Inter-cluster knowledge network indicators.

Network Indicators	**Unit**	**Measurement Definition**
Knowledge inflow, MNC	Network links	Weighted inbound degree centrality of the inventor-assignee network divided by the inventors (INV) (Wasserman and Faust 1994). Indicator is calculated using the iGraph package in R (Csardi and Nepusz 2006)
Knowledge outflow, LAB	Network links per inventor	Weighted outbound degree centrality of the inventor-assignee network divided by the inventors (INV) (Wasserman and Faust 1994). Indicator is calculated using the iGraph package in R (Csardi and Nepusz 2006)
Network reach NET_S	Network links	Inter-cluster co-invention network *simple* degree centrality (Wasserman and Faust 1994), or rephrased: the number of *unique* co-invention relationships a cluster has with other clusters . Indicator is calculated using the iGraph package in R (Csardi and Nepusz 2006)
Network density NET_W	Network links per inventor	Inter-cluster co-invention network *weighted* degree centrality divided by inventors (INV) (Wasserman and Faust 1994), or rephrased: the *total* number of co-invention relationships a cluster has with other clusters relative to the number of inventors (INV) based in the cluster. Indicator is calculated using the iGraph package in R (Csardi and Nepusz 2006)

3.5.5 Path Dependence

Path dependence is thought to be an important determinant of the spatial distribution of innovation activity: locations that have developed the institutions, human resources and social networks that support innovation tend to maintain their innovation advantages for long periods of time because experience, skills, resources, relationships, and reputation accumulate (Crescenzi and Rodríguez-Pose 2011; Frenken, Cefis, and Stam 2015). Path dependence is also addressed in hypothesis 11 and 12. The measurement of path dependence is relatively simple: previous innovation performance (IVP_P) is the value of the dependent variable during an earlier time period. A high correlation between past and present innovation performance suggests strong path dependence. The calculation of inventive performance is explained above in subsection 3.5.1.

Table 3.8: Path dependence indicator.

Path Dependence Indicator	**Unit**	**Measurement Definition**
Previous innovation performance, IVP_P	Citations per inventor	$IVP_P = CIT_P/INV_P$, where subscript-P signifies the indicator values (citations, CIT_P and inventors INV_P) during the directly preceding period.

3.6 Operationalization of Cluster Innovation Performance Model

This section describes the operationalization of the cluster innovation performance model, starting from a conceptual model. The cluster innovation performance model is composed of indicators defined in the previous section (section 3.5) and is used to analyze the relationship between cluster characteristics and cluster innovation performance. The section begins with a conceptual model which describes how cluster characteristics relate to cluster innovation performance based on the hypotheses formulated in chapter 2 (subsection 3.6.1). This is followed by a description of how the model is operationalized, a process that includes a number of empirical tests to identify the optimum model composition (subsection 3.6.2). The section concludes with a presentation of the final implementation of the model, including model equations (subsection 3.6.3) and the selection of the study periods (subsection 3.6.4).

3.6.1 Conceptual Model

Many of the hypotheses outlined in chapter 2 (hypotheses 3-12) explore the relationship between cluster characteristics and cluster innovation performance. These relationships are illustrated in the conceptual model shown in figure 3.1. The conceptual model has three dimensions: a spatial dimension, a sector dimension and a time dimension, which form the external environment that shapes the cluster and cluster innovation performance. The spatial dimension concerns the agglomeration and national innovation system. The sector dimension concerns developments taking place within the sector, including in other clusters, which are connected through global inter-cluster knowledge networks. The time dimension concerns the accumulation of knowledge, skills, experience, relationships, and other factors that create cluster path dependence. All of these factors are seen to influence cluster innovation performance.

Relationships between different cluster characteristics and cluster innovation performance are shown together with the relevant hypotheses, e.g. hypothesis 6 is marked as **H6** in the model diagram. The relationship between cluster innovation performance and agglomeration is the focus of hypotheses 3, 4, and 5. Mutual (two-way) causality with agglomeration is assumed and is represented with a bi-directional arrow. Mutual causality in agglomeration may exist because economies of scale are seen to influence cluster innovation performance, and in the reverse, high innovation performance can attract new firms and researchers to a cluster, thus increasing agglomeration. The relationship between cluster innovation performance and the national innovation system is addressed in hypothesis 6. It is seen as a one-directional influence because of the much larger size of the national innovation system as compared to that of a technology cluster. In a similar way path dependence (hypothesis 11 and 12) is seen as a one-directional influence because of the time-factor involved: the past influences the present. The relationship with global knowledge networks, which is addressed by hypotheses 7, 8, 9, and 10 is also seen as having mutual causality because networks can raise innovation performance, and in the reverse, high innovation performance can attract research collaborations or interest from multinational corporations.

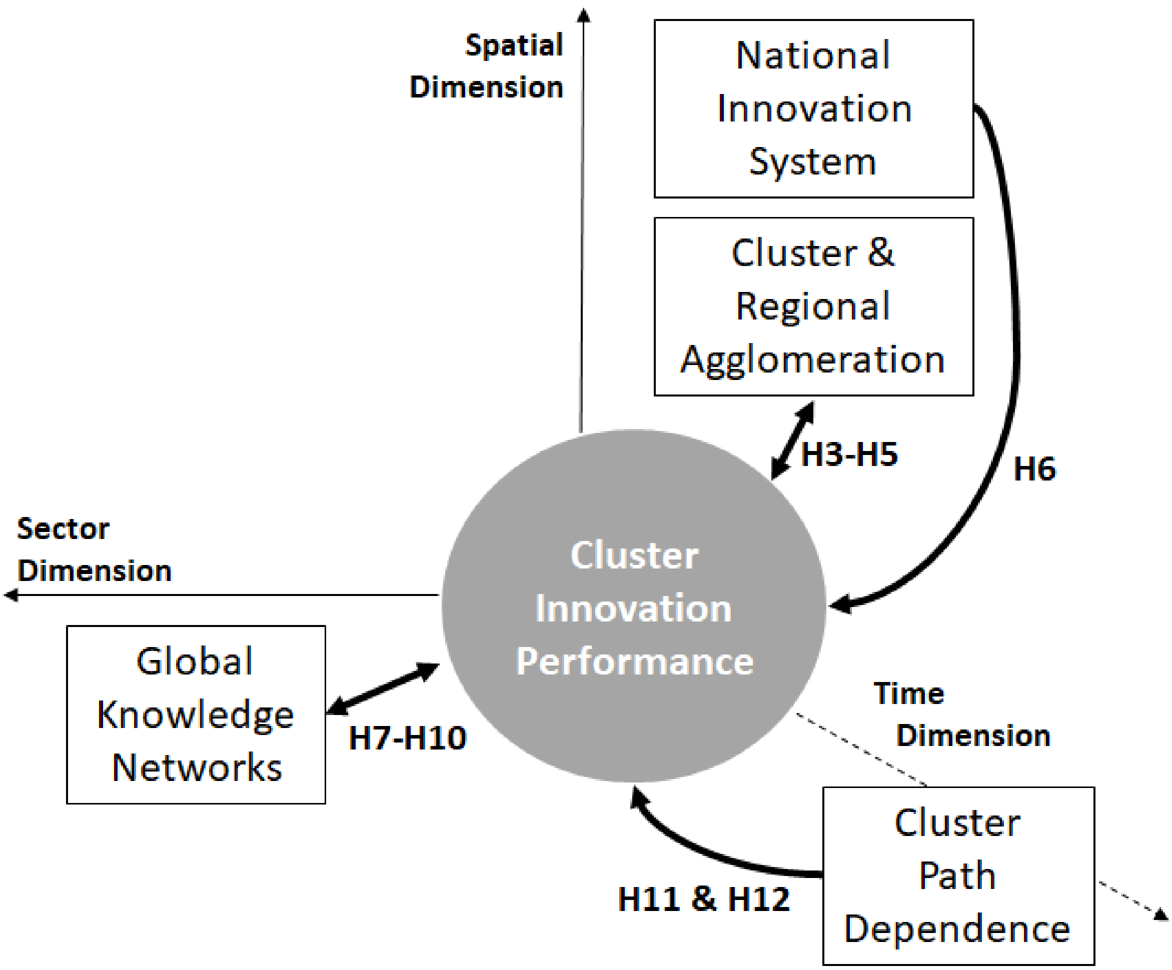

Figure 3.1: Research model.

The combination of many different cluster characteristics in a single model is novel, however the cluster characteristics included in this study were included in some form in earlier knowledge production functions. For example, Charlot, Crescenzi, and Musolesi (2014) included agglomeration, De Rassenfosse and Potterie (2009) national innovation system quality, Ponds, Oort, and Frenken (2009) long-distance knowledge networks, and Crescenzi and Jaax (2017) path dependence as factors in knowledge production functions. To address these diverse cluster characteristics, several partial models are also included in the model estimations. Aside from the diversity of the cluster characteristics, the cluster innovation performance model used in this study also has a different dependent variable: innovation performance. Innovation performance is operationalized in a way that measures the innovation out-performance of a technology cluster relative to the available knowledge inputs (inventors). This approach allows differences in the strength of association between cluster characteristics and cluster innovation performance to be analyzed more clearly, the importance of which is also elaborated upon in section 3.5.1.

3.6.2 Model Operationalization and Testing

Aside from deciding which indicators should be included in the cluster innovation performance model, a number of other modeling decisions must also be made. These decisions are partly guided by previous research and partly depend on empirical model testing using the cluster indicators described in the previous section (section 3.5). Four main model operationalization challenges are addressed in this section: the use of a dummy variables for the knowledge base of the sector, log transformations of indicators, non-linear relationships, and interaction effects.

Dummy variables can be included in the model to account for differences between sectors with a scientific or an engineering and design knowledge base. The large difference in patenting and citation frequencies (Kleinknecht, Van Montfort, and Brouwer 2002; Hall, Jaffe, and Trajtenberg 2005; Kwon, Lee, and Lee 2017) makes it important to explore whether these differences have a statistically significant influence on the innovation performance indicator. The model estimation results in table B.1 (appendix B.1) show that the knowledge base accounts for a relatively small share of the variation in cluster innovation performance. For the health technology and reference high technology sectors is negligible, with adjusted $R^2 = 0.004$ and 0.016 respectively. For the sustainable energy technology sector is slightly higher (adjusted $R^2 = 0.091$). Although the influence of the knowledge base on cluster innovation performance is relatively small, the dummy variable is statistically significant in the sustainable energy and reference high technology models. Therefore, it is included in the final model estimations (see subsection 3.6.3).

The second issue relates to the carrying out of natural logarithmic (log) transformations on indicators. These transformations are also undertaken in other studies in which knowledge production functions are estimated (Acs, Anselin, and Varga 2002; Ó hUallacháin and Leslie 2007; De Rassenfosse and Potterie 2009; Charlot, Crescenzi, and Musolesi 2014). A log-log regression whereby the dependent variable and independent variables are log transformed compares percentage changes in the independent variables to percentages changes in the dependent variable (Changyong et al. 2014). A comparison between a linear regressions and a log-log regression shows a better model fit for the log-log regression, both for the health technology and for the sustainable energy sectors. The adjusted ΔR^2 of the sustainable energy agglomeration and knowledge network model rises from -0.010 to 0.205. See also tables B.2 to B.5 (appendix B.1) for detailed results.

The third model development issue concerns the assumption of non-linear associations between the agglomeration and knowledge network indicators, and cluster innovation performance. From a theoretical perspective agglomeration and knowledge networks can show scale effects (Morgan 2004; Boschma 2005; Capello 2009; Leamer and Storper 2014). To empirically assess the significance of a non-linear relationship, log-quadratic model estimations can be undertaken whereby the independent variables are log transformed and then squared; the dependent variable is only log transformed. The log-quadratic model estimation results suggest that some non-linear relationships may exist. For health technology agglomeration the log-quadratic model provides a negligible improvement in model fit when compared to the log-log model (adjusted $\Delta R^2 = 0.093$ as compared to 0.091). In other instances the log-log model has a better model fit than the log-quadratic model. The results are therefore inconclusive and the simpler log-log model is used for the final model estimations. It is notable that the log-quadratic model show some negative coefficients, suggesting that saturation or declining returns to scale occur. See tables B.2 to B.5 (appendix B.1) for further details.

The fourth and final model estimation issue is the possible existence of interaction effects. The literature suggests that in small clusters very large networks may have an adverse effect on cluster innovation performance (De Propris and Driffield 2005; Fu 2008; Chang, Chen, and McAleer 2013; Ebersberger and Herstad 2013; Hottenrott and Lopes-Bento 2014). Network density and cluster size are therefore compared in a log-log model and in a log-log interaction model, which contains a cluster size-network density interaction term (both log transformed, see tables B.6 and B.7 in appendix B.1). The interaction term is statistically significant for both sectors but does not raise the model explanatory power. The interaction term is therefore not included in the final model estimations.

The model operationalization steps described in this section lead to the inclusion of a dummy variable for the knowledge base of the cluster and a log-log transformation because these yield a noticeable improvement in model fit. The addition of an interaction coefficient and a log-quadratic transformation, which are based on theoretical insights and which produce statistically significant results, do not yield a noticeable improvement in model fit. They are therefore excluded from the final model application, which is described in the next section.

3.6.3 Model Implementation

This subsection describes the cluster innovation performance model as it is implemented in chapters 5, 6, and 7, and includes the list of model indicators, the model formulae, and a discussion of the model diagnostics test results. A summary of the model indicators described in section 3.5 is described in table 3.9, All indicators are log transformed (see discussion in subsection 3.6.2). The model uses summed 2008-2011 data with two exceptions: (i) for national innovation system quality (NSQ) data from the 2011 edition is used and (ii) for previous innovation performance (path dependence, IVP_P) aggregate 2004-2007 data are used (the previous period). The selection of model periods is discussed in subsection 3.6.4, below.

Table 3.9: Cluster innovation performance model indicators with transformations.

Indicator	Description	Variable Type	Transformation
IVP	Innovation Performance	Dependent	Log
D_{KB}	Sectoral knowledge base dummy	Control	None
PAT	Cluster size	Independent	10^{-5} Log
ADJ	Adjacency	Independent	10^{-5} Log
SPE	Regional specialization	Independent	Log
CRP	Corporate research	Independent	Log
NSQ	National innovation system quality	Independent	Log
MNC	Knowledge inflow	Independent	Log
LAB	Knowledge outflow	Independent	Log
NET_S	Network reach	Independent	10^{-1} Log
NET_W	Network density	Independent	Log
IVP_P	Past innovation performance	Independent	Log

The cluster innovation performance model is estimated in five parts. For the first model estimation only **agglomeration** indicators are included in the model. See equation (3.1) where i is the cluster, ϵ_i is the error term and α and β are the model coefficients to be estimated.

$$IVP = \alpha + \beta_1 D_{KB} + \beta_2 PAT + \beta_3 ADJ + \beta_4 SPE + \beta_5 CRP + \epsilon_i \tag{3.1}$$

In the second model estimation only the **national innovation system** indicator is included in the model. See equation (3.2).

$$IVP = \alpha + \beta_1 D_{KB} + \beta_2 NSQ + \epsilon_i \tag{3.2}$$

In the third model estimation only the **knowledge network** indicators are included in the model. See equation (3.3).

$$IVP = \alpha + \beta_1 D_{KB} + \beta_2 MNC + \beta_3 LAB + \beta_4 NET_S + \beta_5 NET_W + \epsilon_i \tag{3.3}$$

In the fourth model estimation only the **path dependence** indicator is included as path dependence tends to have a high correlation with the dependent variable (IVP_P, IVP, R^2 ~0.80). See equation (3.4).

$$IVP = \alpha + \beta_1 D_{KB} + \beta_2 IVP_P + \epsilon_i \tag{3.4}$$

In the fifth model estimation combines the **agglomeration and knowledge network** indicators with the national innovation system indicator. Due to the often high correlation between network reach and cluster size (NET_S, PAT, R^2 ~ 0.80), network reach is removed from the model. See equation (3.5) (see also correlation matrices in tables B.8, B.12 and B.16, appendix B).

$$IVP = \alpha + \beta_1 D_{KB} + \beta_2 PAT + \beta_3 ADJ + \beta_4 SPE + \beta_5 CRP + \beta_6 NSQ + \beta_7 MNC + \beta_8 LAB + \beta_9 NET_W + \epsilon_i \tag{3.5}$$

The models are estimated using Ordinary Least Squares (OLS) regression. OLS regression is considered a "standard" regression technique widely applied in different areas of science, ranging from political science (Krueger and Lewis-Beck 2008) to bio-statistics (Harrell 2015). The validity of OLS regression estimations are subject to a number of assumptions, including the absence of multicollinearity among variables and normally distributed residuals (Harrell 2015). If the OLS assumptions are violated, alternative regression techniques such as Quantile Regression (QR) or Maximum Likelihood (ML) can be used (Harrell 2015). If there are endogeneity issues, Generalized Method of Moments (GMM) model estimation techniques can also be applied (Hall 2005).

To confirm the validity of the OLS assumptions, model diagnostics for the health technology, sustainable energy and reference high technology regression models are available in tables B.11, B.15 and B.20 (appendix B). The model estimation results are within the accepted boundaries for multicollinearity (Variance Inflation Factor < 2) and normally distributed residuals (Shapiro-Wilk test $p < 0.10$). Heteroscedasticity is not within the accepted boundaries for most model estimations (Breusch-Pagan $p < 0.10$) except for the health technology sector. Heteroscedasticity issues mean that the values of the coefficients may be biased, although this does not appear to influence the statistical significance of correlation in a meaningful way (Lumley et al. 2002; Meuleman, Loosveldt, and Emonds 2015). Therefore, the basic assumptions of OLS regression are being met, and the correlations in the model results are robust.

When applying OLS, *robust* standard errors are often used. Robust standard errors are suitable for studies that consist of a relatively small sample of a much larger normally distributed population. In this study the complete worldwide population of clusters is studied, and some of the cluster indicators *do not* appear to be normally distributed, hence the "original" OLS standard errors are used in this study (Wooldridge 2009, 268).

Statistical summaries of the model indicators and full model estimation results (including standard errors) are discussed in their respective chapters for the health technology (chapter 5), sustainable energy (chapter 6), and reference high technology sectors (chapter 7), and supplementary model estimations are presented in appendix B.

3.6.4 Period Selection

The selection of the study periods is an important modeling decision because of the dynamic nature of the sectors being studied and the desire to make cross-sectoral comparisons. In this study three four-year periods are used. The latest period covers patents which were filed during 2008-2011 and which were eventually granted.

A four-year period is chosen because patent output data often shows considerable variation from year to year, mainly because patents are often applied for in groups near the end of a project or research phase (Gautam, Kodama, and Enomoto 2014). This makes it useful to take an average over a longer period of time. To compare, Alcácer and Zhao (2016) also use a four-year period and Ó hUallacháin and Leslie (2007) use three years. Charlot, Crescenzi, and Musolesi (2014) use 10 years, which would be too long for this study, which also aims to show temporal changes.

The selection of specific time periods that match important sectoral events is complicated by the fact that the research concerns multiple sectors and sub-sectors. For this reason the most recently available four-year period is selected (2008-2011), and then earlier four-year periods are chosen (e.g. 2004-2007, 2000-2003, etc.). During these periods some notable economic crises occurred, including the 2000 "dot-com" crash and the 2008 mortgage crash, which both started in the United States but had worldwide repercussions.

Describing 2008-2011 as "most recent" (while writing this dissertation in 2018) should be understood within the context of the use of patent grants as the main data source. There can be a delay of several years between patent application and patent grant. To ensure a complete data set whereby an estimated 90% or more of patents are granted for a particular year, 2011 is considered to be the most recent year at the time of writing. A related concern is the year of the patent application and its meaning: is it equivalent to the year during which the innovation activity took place? Prior research on this subject suggests that a patent is applied for between 1 to 3 years after the actual research has taken place, with shorter patent submission times in high technology sectors and in advanced economies (Hall, Griliches, and Hausman 1984; Greif 1985; Kondo 1999; Igor 2005; Gurmu and Pérez-Sebastián 2008). Therefore, each period (e.g. 2008-2011) may describe a slightly earlier period of research and innovation activity.

3.7 Summary and Discussion

Both the cluster identification method and cluster innovation performance model described in this chapter offer a number of improvements compared to earlier methodologies. This section will focus on the cluster innovation performance model; the cluster identification method is discussed in detail in the next chapter (chapter 4). The cluster innovation performance model differs from earlier knowledge production functions in three main ways: the development and application of a unique global database of technology cluster metrics based on patent data, the use of certain novel indicators that describe cluster characteristic, and the use of a novel dependent variable that measures cluster innovation out-performance, changing how innovation performance is conceptualized and measured.

The database of technology cluster metrics developed as part of this study is unique in a number of ways. First, it provides information at the spatial scale of clusters and is global in scope. Second, it provides information about technology clusters in niche sectors such as wind turbines or biofuels, as well as broader technology clusters such as pharmaceuticals or electronics. Third, the indicators capture many different cluster characteristics, including cluster size, cluster knowledge network relations, innovation performance, and cluster composition in terms of innovation actor types (corporations, universities, etc.). Fourth, the information can be gathered for multiple periods, in the case of this study three four-year periods from 2000-2011. The scale, scope, sectoral specificity, diverse cluster characteristics, and extended time periods make the database of technology cluster metrics a unique resource. The database can be used for descriptive analysis, monitoring cluster developments, and quantitative analysis, such as for example in a regression models of cluster innovation performance.

Five novel indicators are introduced in this study: adjacency, regional specialization, corporate research, knowledge inflow, and knowledge outflow. The indicators describe cluster characteristics that have not previously been applied in knowledge production functions, or which were operationalized in different ways. Adjacency is a familiar concept in spatial analysis, however it is operationalized differently in this study. Rather than measuring the "spillover" of innovation performance from neighboring regions (Ó hUallacháin and Leslie 2007; Charlot, Crescenzi, and Musolesi 2014), adjacency is operationalized as an additional scale-based agglomeration indicator that measures the size of nearby same-sector clusters. This different approach is needed because of the different way in which clusters are identified in this study, and it provides insight into broader "regional" agglomeration beyond the boundaries of the cluster. Regional specialization, another familiar concept, had not previously been incorporated in knowledge production functions because these functions were typically applied to the region as a whole (all sectors) and not to sector-specific clusters. Regional specialization is a measure of the relative size of the sector compared to all sectors in a region. Corporate research was included as an indicator to represent the inverse of government and university-based research output, which Ó hUallacháin and Leslie (2007) concluded has a negative influence on cluster innovation performance. From a theoretical perspective corporate research is seen as a measure of a cluster's absorptive capacity (Fu 2008; Lau and Lo 2015). Knowledge inflow and outflow were incorporated to capture the influence of "reverse" knowledge flows (Frost and Zhou 2005), and were not previously incorporated into knowledge production functions.

The sixth novel indicator, the dependent variable of the cluster innovation performance model, is unique in its measurement approach and in its conceptualization of innovation performance. In this study cluster innovation performance is measured based on patent citations instead of patent counts. Citations represent the value of the innovations that were patented (Hall, Jaffe, and Trajtenberg 2005). The number of patent citations is divided by the number of inventors, a measure of the available knowledge inputs in the cluster. The innovation performance model therefore predicts the innovation out-performance of a cluster based on its cluster characteristics. The ability of the model to predict innovation out-performance varies depending on the sector being analyzed. The model's predictive power is understandably lower than that of knowledge production functions, which predict knowledge production based on the available knowledge inputs (typically the number of researchers/inventors), which are known to be highly correlated (Hagedoorn and Cloodt 2003). Innovation performance, on the other hand, is a more precise dependent variable because the very high correlation between knowledge inputs and knowledge production is eliminated from the model, revealing the role of other cluster characteristics in explaining differences in cluster innovation performance. The combination of a novel database of cluster metrics, novel indicators and a novel approach to modeling cluster innovation performance provides a fresh empirical perspective, which is applied in chapters 5-7 to the health technology, sustainable energy technology, and general high technology sectors.

Chapter 4

Cluster Identification

Note: An earlier version of the methodology described in this chapter was published in *Scientometrics* (Stek 2021).

4.1 Introduction

This chapter provides a detailed description of the cluster identification methodology designed as part of the current Ph.D. research. It expands on the brief overview of the cluster identification methodology presented in chapter 3. As noted earlier, the innovation literature attaches great importance to the sub-national regional scale, as well as global connections, and competition between clusters, as factors that determine or coincide with high cluster innovation performance (Porter 2000; Fujita, Krugman, and Venables 2001; Simmie 2004; Gertler and Wolfe 2006). However, global datasets at the sub-national or clusters scale are typically lacking. Even if they do exist, the use of sub-national administrative divisions may show a poor overlap with actual innovation activity (Alcácer and Zhao 2016; Van Egeraat et al. 2018). Furthermore, the spatial scale of national sub-divisions can vary greatly from country to country, making international sub-national comparisons difficult. This creates a significant knowledge gap for researchers aiming to study cluster-based phenomena on a global scale.

A potential solution for the identification of clusters on a global scale is the use of patent data, which contains micro-spatial information. First, patenting plays an important role in the innovation process because patents grant monopoly rights to inventors over a particular idea or design for a fixed period of time. As a result, patent output is closely correlated to other measures of innovation performance such as R&D expenditure or the number of active researchers (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004; Squicciarini, Dernis, and Criscuolo 2013). Alcácer and Zhao (2016) therefore conclude that the spatial concentration of patenting is a clear indicator of a technology cluster's existence. Second, the micro-spatial information contained in patent documents, such as addresses of inventors, enables the geo-location of patents at a sub-national spatial level, typically at the level of a town or city, allowing spatial concentrations of patents to be identified. Alcácer and Zhao (2016) describe the identification of clusters from patents as an "organic" cluster identification methodology. The methodology described in this chapter builds on that approach by using heat maps (kernel density estimation) to identify "hot spots" of innovation activity, which are identified as clusters once a particular spatial concentration threshold is exceeded. Heat maps are widely used in spatial analysis in fields as diverse as epidemiology, archaeology, and transportation safety (Bithell 1990; Baxter, Beardah, and Wright 1997; Anderson 2009), but they appear to be absent from scientific studies of innovation activity. This chapter demonstrates that using heat maps is an effective way of identifying technology clusters and that the methodology's performance in terms of "correctly" identifying clusters matches or exceeds the performance of alternative approaches.

The chapter begins with a review of earlier studies in which patent data are used to identify technology clusters (section 4.2). Based on this review a set of design criteria is formulated for a new cluster identification methodology (section 4.3). The main steps of the methodology, including data selection, and the process of geocoding patents is discussed next (section 4.4). Thereafter a sensitivity analysis is carried out to find suitable parameter values for the cluster identification algorithm (section 4.5). The chapter ends with a discussion in which the new methodology is evaluated against the design criteria outlined earlier in the chapter (section 4.6).

4.2 Overview of Cluster Identification Methodologies and Current Limitations

Researchers of technology and innovation seeking to understand the spatial dynamics of innovation activity at the cluster level often face data-related challenges. This section provides an overview and limitation of the data sources available for cluster identification and analysis. The two types of data sources are regional statistical data and clusters identified from scientometric data (including patents). There are two main approaches to identifying clusters: relative spatial concentration within pre-defined boundaries and the "organic" cluster identification method based on real spatial concentration (Alcácer and Zhao 2016).

The Organisation of Economic Cooperation and Development (OECD) and European Union (EU) publish sub-national regional statistical data that covers aspects of research and innovation in multiple countries. However, these datasets typically exclude emerging sectors such as renewable energy technologies and fast-developing non-OECD countries in Asia and elsewhere. Furthermore, detailed statistics on technology and innovation tend to be available only at the national level. Alternatives statistical databases such as those from the World Bank and United Nations Education, Scientific and Cultural Organisation (UNESCO) Institute for Statistics tend to cover a greater number of countries, but they do not provide sub-national data and often have more limited statistics on technology and innovation. This data deficit makes it difficult, if not impossible, to explore a sector's true global spatial distribution using statistical databases.

Patents are frequently used as a proxy for innovation output, including at the sub-national level of regions or cities (Bergquist, Fink, and Raffo 2017; Crescenzi and Jaax 2017). The use of patent data can overcome some of the limitations of statistical data: patent data are global in scale and patents often contain geographical information such as an inventor address, which allows for the identification of a city or other sub-national spatial unit (Alcácer and Zhao 2016; Bergquist, Fink, and Raffo 2017). Patents are the "paper trail" of innovation activity (Jaffe, Trajtenberg, and Henderson 1993) and patent data has been widely used in spatial studies of innovation since the 1990s, whereby patent counts typically serve as a proxy for innovation activity in a particular area or region Charlot, Crescenzi, and Musolesi (2014). This makes patents a very promising source of data to monitor global innovation activity at a sub-national scale.

Despite its potential, the use of patent data also raises methodological concerns. Patent count data are sensitive to differences in patenting propensity between industry sectors, which means that a gross patent count is not necessarily an accurate reflection of innovation activity (Arundel and Kabla 1998; Kleinknecht, Van Montfort, and Brouwer 2002; Hall, Jaffe, and Trajtenberg 2005). Another concern is that there are significant differences in patenting propensity between countries due to economic and governance factors (Yang and Kuo 2008; De Rassenfosse and Potterie 2009). There is also a home bias effect, whereby the number of patents and patent citations from the home country are inflated in the home country's patent database because local inventors will usually patent their inventions locally first. Local patents are also cited more frequently, both by local inventors and by local patent examiners (Potterie and De Rassenfosse 2008; Bacchiocchi and Montobbio 2010). Using patent data from multiple countries also has drawbacks because it introduces variations in patent evaluation standards: different countries maintain different criteria for granting patents. This difference in standards inflates the number of granted patents in some countries, such as China, Japan, and South Korea, when compared to the United States or the European Patent Office, which maintain more stringent criteria (Laurens et al. 2015; Toivanen and Suominen 2015). Especially if patent data are used in the measurement of various cluster characteristics, such concerns must be addressed.

There are two approaches in the economic geography literature for the identification of technology clusters: (i) by measuring relative concentration within predefined spatial boundaries, and (ii) using the actual spatial concentration of specific points within a data set (e.g. plant locations, inventor locations, etc.) to define new boundaries of high spatial concentration (Clark and Wójcik 2018). This last methodology is also described as "organic" cluster identification (Alcácer and Zhao 2016).

The first approach involves identifying clusters using pre-existing statistical boundaries such as: states, Metropolitan Statistical Areas (MSA, United States), Nomenclature of Territorial Units for Statistics (NUTS, European Union), statistical divisions and subdivisions (Australia), prefectures (Japan), departments (France), etc. The use of pre-existing boundaries has advantages and disadvantages. The advantage of pre-existing boundaries is that scientometric data can be coupled to other statistical data such as R&D expenditure, labor market information, income levels, etc. For that reason Ó hUallacháin and Leslie (2007), Spencer et al. (2010) and Charlot, Crescenzi, and Musolesi (2014) all utilize pre-existing regional boundaries as cluster boundaries.

The disadvantage of using pre-existing boundaries is that the scales of the statistical boundaries can vary significantly, especially when international comparisons are attempted (a "province" in China is many times larger than a "province" in the Netherlands or South Korea). Furthermore, a concentration of R&D activity may spill over into multiple pre-existing boundaries by being located in multiple provinces/states, thus diluting it. R&D activity can also occur in a small part of a province/state, which can then dilute the concentration of innovation activity for that province/state. An average value for a particular area may hide large differences between different locations within it.

An alternative to using pre-existing statistical or administrative boundaries is to identify cluster boundaries based on the actual concentration of patenting. This "organic" clustering approach (Alcácer and Zhao 2016) is especially advantageous in international research because it overcomes the challenge of using differing statistical boundary sizes for different countries. The approach also avoids potential dilution or distortions due to the use of inappropriate boundaries (Alcácer and Zhao 2016; Bergquist, Fink, and Raffo 2017; Van Egeraat et al. 2018).

However, there are some potential pitfalls from the use of patents for cluster identification. Stek (2019) shows that it can lead to the identification of (very) large clusters, because R&D activity tends to follow patterns of urbanization, which can yield very large cluster-corridors, such as from Boston to Philadelphia via New York (United States), Tokyo-Nagoya (Japan), and even Cologne-Frankfurt-Zurich (Europe), which stretch the definition of "spatial proximity" and thus what constitutes a cluster. This requires the careful calibration of a clustering algorithm to ensure that the identified clusters are accurate, something that can be achieved by imposing a maximum cluster size, a technique used in identifying spatial clusters of infectious diseases (Han et al. 2016; Ma et al. 2016).

Another problem is the choice of data source. Bergquist, Fink, and Raffo (2017), in a study published by the World Intellectual Property Organization (WIPO), use the WIPO Patent Cooperation Treaty (PCT) database, which appears to inflate the patent output of clusters in countries such as China, Japan, and South Korea (Laurens et al. 2015), and excludes Taiwan, presumably for political reasons.

To assess the quality of their organic clustering algorithm, Alcácer and Zhao (2016) propose a benchmark based on collaboration distance to see if a higher number of collaborators located in close proximity to each other are also found within the same cluster. Alcácer and Zhao (2016) calculate which percentage of co-inventors located within 10-20 mi (16-32 km) from each other are classified as being within the *same* cluster, and which percentage of co-inventors located more than 20 mi (32 km) apart are located in *different* clusters. While the 16 and 32 km distance is somewhat arbitrary, it does provide a uniform benchmark for comparing the performance of different clustering methodologies. Alcácer and Zhao (2016) use this approach to show that organic cluster identification methodologies perform better than pre-defined cluster boundaries.

4.3 Design Criteria

The overview presented in the previous section shows some clear advantages of using an organic cluster identification methodology, but it also highlights a number of limitations that a new and improved methodology should address. These limitations are: (i) accurately linking cluster patents to innovation performance without incorporating home biases and other measurement errors (ii) ensuring that the identified cluster boundaries are reasonable in their spatial scale, and (iii) verifying that the identified cluster pattern is an accurate reflection of real spatial interactions at the cluster scale. These three limitations are translated to design criteria for the new clustering methodology, along with a desire to ensure the methodology can be widely used by policy makers and other interested parties.

1. Use a single source of patent data to ensure a uniform standard of patent evaluation (Laurens et al. 2015; Toivanen and Suominen 2015), but apply some kind of correction to address the problem of the home bias effect (Bacchiocchi and Montobbio 2010).

2. Analyze single industries or sectors to address the problem of varying patenting propensities (Kleinknecht, Van Montfort, and Brouwer 2002; Hall, Jaffe, and Trajtenberg 2005).

3. Optimize the clustering algorithm parameters to identify realistic clusters, such as imposing a maximum cluster size (Han et al. 2016; Ma et al. 2016).

4. Performance of the new clustering algorithm is similar or better than those of existing methodologies (fewer errors), especially when compared to using predefined cluster boundaries.

5. The clustering algorithm is automated and underlying data are publicly available so that it can be used for the mapping and observation of technology clusters by policy makers and other stakeholders.

The data processing methodology presented below (section 4.4), and the calibration and sensitivity analysis that follows (section 4.5), are guided by these design criteria. The methodology is evaluated against the design criteria in the discussion (section 4.6).

4.4 Data and Data Processing

This section describes the steps taken to prepare the patent data before the clustering "heat map" algorithm is applied. First the source of patent data is discussed (subsection 4.4.1), followed by the patent geocoding process (subsection 4.4.2), the home bias correction process (subsection 4.4.3), and the sectoral delineation of patent data. The calibration and sensitivity analysis of the "heat map" algorithm itself is described in section 4.5

With regard to the clustering algorithm, all data processing, calculations, and spatial analysis in this chapter and in later chapters are performed using a combination of R statistical software (R Core Team 2019), MySQL database software (Widenius, Axmark, and Arno 2002) and QGIS spatial analysis software (QGIS Development Team 2019). The MySQL database is used to store and analyze the patent data. R is used to extract and organize this data and to transform it into spatial data which can then be processed and analyzed in QGIS. The heat map interpolation and cluster identification is carried out in QGIS. Spatial cluster data are re-imported into R for further analysis.

4.4.1 Patent Data

Patent databases contain patents from different countries, provide a significant level of detail about the technologies involved, cover long time series during which evaluation criteria used by patent examiners have remained essentially unchanged and patents contain information about the inventors and patent owners (Schmoch 1999; Acs, Anselin, and Varga 2002). This means that patents can provide a large amount of information at a temporal and spatial scale unmatched by other data sources and be used as raw data for a range of useful applications, as shown earlier in table 3.1. However, challenges arise when deciding which patent database to choose (or whether to use multiple patent databases) and how to address the home bias effect (Yang and Kuo 2008; Bacchiocchi and Montobbio 2010).

The most important patent databases are those of the USPTO, EPO and the Japan Patent Office (JPO) because these countries are important markets for, and important generators of, high-technology inventions (Frietsch and Schmoch 2009; Kim and Lee 2015). Choosing a single patent database introduces a particular country's home bias, but the advantage is that a single patent evaluation standard is followed, which improves the validity of making international comparisons (Criscuolo 2006; Toivanen and Suominen 2015).

An alternative to using a single database are the database of "triadic patents." Triadic patents appear in the databases of the USPTO, EPO and JPO. This approach appears to eliminate any home bias effect, but the number of triadic patents is very small, as only the most valuable patents are filed at all three patent offices (Criscuolo 2006). Therefore, significant patenting activity can go undetected, especially innovation activity from emerging countries where patent quality is often lower (Frietsch and Schmoch 2009). As an example, an emerging economy such as India had 2,669 patent grants at the USPTO (2016) but only 359 triadic patents (13%) in the same year (source: OECD, 2016).

Previous technology cluster identification studies have used a variety of scientometric databases. Alcácer and Zhao (2016) and Bergquist, Fink, and Raffo (2017) use two global patent databases, the Derwent World Patents Index™ and Patent Cooperation Treaty (PCT) database. Global databases carry a degree of bias, notably the very high presence of South Korean, Japanese and Chinese patents due to different rules for patent approval in those countries (Laurens et al. 2015; Boeing, Mueller, and Sandner 2016). This is problematic for the purposes of identifying and quantifying clusters, because it overstates the cluster size in these countries. Bergquist, Fink, and Raffo (2017), using WIPO's PCT database, estimates that of the 10 largest clusters, 6 are in Japan, China and/or South Korea. The present study places only 3 of the 10 largest clusters in these three countries and also includes Taipei, Taiwan as a top 10 cluster. The data used by Bergquist, Fink, and Raffo (2017) seems to exclude Taiwan, which is not a signatory to the PCT and is therefore excluded from the database. Catini et al. (2015) uses the PubMed scientific publications database, which has as a limitation in that it is only relevant for the medical sciences.

This study uses a national patent database because of the consistency in standards (Toivanen and Suominen 2015) which is important when making quantitative comparisons between countries. However, national databases suffer from a home bias effect (Potterie and De Rassenfosse 2008; Bacchiocchi and Montobbio 2010), an issue addressed in subsection 3.3.3. Among the three major national patent databases (EPO, JPO, USPTO) the USPTO has the greatest international coverage (Kim and Lee 2015) and it is therefore selected in this study. Specifically the PatentsView database is used, which is published by the Office of Chief Economist in the USPTO and contains data on 6,647,699 patent grants from the USPTO (May 2018 edition).[1] The delay between patent application and grant means that the most recent year for which full patent grant data are available is 2011 (as at time of writing of this dissertation).

The PatentsView database contains basic bibliographic information of patent documents such as patent identification numbers, application dates, inventors and assignees, the city, state and country of inventors and assignees, and patent citations, along with technological classifications. The citations a patent receives are from other granted patents and can serve as an indicator of patent value (Hall, Jaffe, and Trajtenberg 2005). In this study patent citations are used as part of the dependent variable. Patent inventor and assignee addresses and technological classifications are essential for the cluster identification process. The technological classifications link a patent to a particular industry based on a concordance table. The address enables the identification of a geographic location of where the innovation activity took place that led to the patent application.

[1] The PatentsView database tables can be downloaded at: http://www.patentsview.org/download/ (accessed 24 March 2019)

4.4.2 Patent Geocoding

Patent geocoding is the process of assigning spatial coordinates to an address listed on a patent document. In deciding which address to use to identify clusters, there is a non-trivial reason for using the addresses of inventors (individuals who carried out the R&D) rather than assignees (typically firms that financed the R&D). Inventors' location provides information about where the R&D took place whereas the assignee location provides information about who owns the inventions. Given the globalization of R&D activity, assignees and inventors are frequently found in different countries. Assignees may also be located in tax havens such as the British Virgin Islands or Cayman Islands, which have very small economic and R&D activity. Accordingly, inventor location is used to identify R&D activity because it reflects the most likely "true" location of where the R&D was carried out.

To identify areas of high R&D activity, inventor address information is converted into coordinates through a geocoding process. For example, the address "Delft, The Netherlands" is converted into the coordinates 51.9995142, 4.2938295. Although the PatentsView database does provide coordinates for patent addresses, upon closer examination a number of these appear to be inaccurate. There are cases of patent coordinates being in a different country than the country listed in the address. There are also instances where coordinates are based on incomplete address information and therefore based on a country or state level, and not at that of a town or city. For example, a patent with an address of only "California" or "Canada" is geolocated in the geographic center of the state or country concerned, distorting the data. By screening the PatentsView database for these errors, it appears that approximately 6.5% of PatentsView addresses worldwide have such an issue. They are geocoded once again in this study. The re-geocoding process is elaborated upon in table 4.1. Re-geocoding raises the number of addresses that can be accurately geolocated from 93% to 96% of the PatentView database. Inventors or assignees whose address cannot be accurately geolocated are removed from the database, a measure which affects fewer than 1% of patents.

Table 4.1: Patent address geocoding method used in this study.

Step	Geocoding process
1	Addresses in countries or territories which are less than 20,000 km^2 in size are automatically assigned a single coordinate location. The largest entity among this group is New Caledonia (18,575 km^2), also included are entities such as Kuwait, Montenegro, Qatar, Cyprus, Puerto Rico, Luxembourg, Hong Kong and Singapore.
2	Coordinates are checked based on (i) whether they are located in the same country as the country stated in the original address and (ii) whether they are based on a country-level or state-level location, rather than a city-level location. Any mis-coded or uncoded addresses (lacking coordinates) are then subject to (re)geocoding in step 3.

Step	Geocoding process
3	Addresses are geocoded using the open-source TwoFishes geocoding application (using index files updated on 2015-03-05).[2] TwoFishes is a course spatial geocoder and is used and maintained by FourSquare Labs Inc., a company that operates a popular local search-and-discovery service mobile application. An important advantage of TwoFishes is that it is open source and therefore its geocoding results are reproducible. Twofishes has scientific credibility and has been used in published and peer-reviewed scientific papers (Sessions et al. 2016; Hamstead et al. 2018) and it is listed in *The SAGE Handbook of Social Media Research Methods* (Sloan and Quan-Haase 2017).
4	As an added screening, clusters identified in areas with no significant population center are subject to additional scrutiny and often lead to the identification of miscoded locations (false positives). This problem seems to occur primarily in South Korea and Japan where 11 miscoded locations are identified, including Daejeon, Yokkaichi, Kurashiki, Nara, Sendai, Kanagawa and Tochigi. Catini et al. (2015) also noted challenges in geocoding Japanese and Korean addresses. These miscoded locations are manually corrected in the geolocation database by changing the coordinates of the 11 locations.

4.4.3 Location Weighting and Home Bias Correction

After geolocating inventor addresses, a location weighting and home bias correction are carried out, for patents and citations. The location weighting is calculated through the fractional counting of patents and represents the magnitude of the innovation activity in a particular location. The home bias correction factor adjusts the number of patents and citations counted outside the United States to enable a comparison between American and other clusters.

The fractional counting of patents for the location weighting works as follows. Each identified location i has a weighting (PTW_i) based on the number of inventors with an address in a location (INV_{ij}) divided by the total number of inventors of the patent ($INVT_j$). Thus if all the patent's inventors are in the same location, $PTW_i = 1$. This amount is then summed for all patents k for each location location i, as described in (4.1). An example calculation: a patent with 3 inventors, 2 of whom have an address in "Delft, The Netherlands" would add a weighting of $2/3 = 0.67$ to the location of "Delft, Netherlands" (51.9995142, 4.2938295).

$$PTW_i = \sum_{k=0} INV_{ij}/INVT_j \tag{4.1}$$

Once the location weighting is calculated, a home bias correction can be performed. The home bias of the USPTO data used in this study means that patents with inventors located in the United States are over represented in terms of the number of patents appearing in the database and the number of citations per patent (Potterie and De Rassenfosse 2008; Bacchiocchi and Montobbio 2010). The home bias is compensated for by correcting the patenting frequency and citations frequency of non-United States invented patents.

The correction factors (patents and citations) are calculated by comparing United States-invented patents to Japan-invented patents in the USPTO database. Japan is chosen because its qualitative patenting profile is most similar to that of the United States (Mancusi 2008; Toivanen and Suominen 2015). Therefore, differences between Japan and United States-invented patents can be attributed primarily to the home bias effect, rather than to other technological or economic factors. The correction factors are calculated based on national averages to increase robustness and avoid potential sectoral distortions: while both countries have a similar patenting profile at the aggregate level, notable sectoral differences likely exist, and therefore a correction factor based on sectoral data are likely less robust.

The patent output correction factor (COR_{PAT}) is based on a comparison of the ratio of researchers to patent output for Japan and the United States. If there is no home bias effect, advanced economies with a comparable patenting profile should have a very similar ratio of patent output to researchers, because the same inputs (researchers) should lead to similar outputs (patents). COR_{PAT} is calculated using equation (4.2), whereby PAT_{US} is total number of United States-invented patents, RES_{US} is the total number of researchers in the United States, PAT_{Japan} is the total number of Japan-invented patents and RES_{Japan} is the total number of researchers in Japan. The number of researchers and USPTO patent count data (by inventor residence) are obtained from the UNESCO Institute of Statistics[3] and the USPTO PatentView database, respectively.

$$COR_{PAT} = (PAT_{US}/RES_{US})/(PAT_{Japan}/RES_{Japan}) \tag{4.2}$$

The citations per patent correction factor (COR_{CIT}) is based on comparing citations and patents in the United States and Japan. Advanced economies with a comparable patenting profile should have a very similar average patent quality and patent citation ratio at the same patent office. Therefore, differences in the patenting citation ratio using USPTO data can be attributed to home bias. COR_{CIT} is calculated using equation (4.3), whereby CIT_{US} is total number of citations received by United States-invented patents, PAT_{US} is the total number of United States-invented patents, CIT_{Japan} is the total number of citations received by Japan-invented patents and PAT_{Japan} is total number of Japan-invented patents. The variables are calculated using 1996-2011 data from the PatentView USPTO database.

$$COR_{CIT} = (CIT_{US}/PAT_{US})/(CIT_{Japan}/PAT_{Japan}) \tag{4.3}$$

Correction factors are calculated for four periods, as shown in table 4.2 below. The values show a discernible trend of falling home bias in the patent output correction factor (COR_{PAT}) and rising home bias in the citations per patent correction factor (COR_{CIT}). This trend is also visible when the coefficients are calculated on an annual basis, or when using data for other countries (Germany, South Korea, Taiwan) and therefore these changes appear to be systematic, although their cause is unknown. Because of this trend, different correction factor values are used for each period. The correction is made by multiplying non-United States patent or citation counts by the relevant correction factor. The correction factors are selectively applied throughout the study whenever patent or citation counts are used.

[3]Database titled 'Science,technology and innovation: Gross domestic expenditure on R&D (GERD), GERD as a percentage of GDP, GERD per capita and GERD per researcher' is available from: http://data.uis.unesco.org/ (last accessed 1 October 2019)

Table 4.2: Correction factors for four periods (own calculations).

Period	COR_{PAT}	COR_{CIT}
1996-1999	1.93	1.89
2000-2003	1.60	2.05
2004-2007	1.45	2.14
2008-2011	1.29	2.47

In case of the earlier example for Delft, Netherlands, (51.9995142, 4.2938295) in the main text, the corrected patent weight ($PTW'i$) would be calculated as shown in equation (4.4), Whereby k is the total number of patents j in a location i with a particular share of inventors (INV) relative to the total number of inventors of the patent ($INVT_j$) and COR_{PAT} is the patent correction factor as shown in table 4.2.

$$PTW'_i = \sum_{k=0} INV_{ij}/INVT_j \times COR_{PAT} \tag{4.4}$$

4.4.4 Sectoral Delineation

An important advantage of using patent data is the ability to identify patents related to specific industries or technologies. The PatentsView database, used in this study, contains various technological classifications. In addition to national classifications, the International Patent Classification (IPC) and Collaborative Patent Classification (CPC) are also available. The IPC system is maintained and regularly updated by the World Intellectual Property Organization (WIPO) in Geneva, of which most national patent offices are a member. The CPC is a joint initiative of the USPTO and EPO and involves the creation of new technology classes for renewable energy technologies and other green house gas reducing inventions (Y-classes). Technological classes are assigned by patent examiners at the respective patent office at which the patent is filed.

To link patent technology classifications to specific industry sectors requires a concordance table. Using a probabilistic methodology based on text mining, Lybbert and Zolas (2014) have developed technology-industry concordance tables that incorporate all levels of industry classifications, including for the International Standard Industry Classification (ISIC). ISIC is a classification maintained by the United Nations Department of Economic and Social Affairs Statistics Division (UNSD) in New York and is used by countries to classify economic activity. The ISIC system consists of a range of groups and (sub)divisions. Because the ISIC system is applied to the entire economy and used by national and international government agencies, it is only updated every few years. Therefore, ISIC lacks coverage of niche or emerging sectors. This void can be filled by the identifying such niche sectors using specific patent classes. Some examples follow which are relevant for this study. The Organization for Economic Co-Operation and Development (OECD) identifies patents related to emerging high technology industry sectors, including Nanotechnology and Biotechnology (OECD 2013). The CPC has the aforementioned Y-classes related to Photovoltaics, Wind Turbines, and other emerging green house gas-reducing technologies (Leydesdorff et al. 2014). The Australian patent office, IP Australia in Canberra, identifies a number of niche sectors related to the growth of the Australian medical devices and pharmaceuticals sectors, including the medical life sciences in some of its research reports (IP Australia 2014, 2015).

Emerging health technology and sustainable energy technology sectors are the focus of this study. Two emerging healthcare sectors are identified: medical devices and the medical life sciences. The medical devices sector is defined by ISIC group 266 (manufacture of irradiation, electromedical and electrotherapeutic equipment) and group 325 (manufacture of medical and dental instruments and supplies). The medical life sciences sector is identified based on the CPC classifications proposed by IP Australia (2015), which partially overlaps with the CPC codes linked to biotechnology (OECD 2013) and pharmaceuticals (Lybbert and Zolas 2014). Seven sustainable energy technology sectors are also included in the study: biofuels, electric vehicles, energy storage, fuel cells, hydrogen technology, photovoltaics and wind turbines. All sustainable energy sectors are identified based on the CPC Y-class codes. All sectors with 600 or more patent grants between 2008-2011 are included in the study. This minimum threshold is set to ensure sufficient data are available to carry out spatial and network analysis. Table 4.3 provides an overview of the ISIC or CPC classes for the sustainability technology sectors

In addition to the aforementioned sustainability technology sectors ten reference sectors are also included in the study. They are used as a benchmark in chapter 7. Among these benchmark sectors there are eight high-technology and R&D intensive ISIC sectors (Galindo-Rueda and Verger 2016) and Biotechnology and Nanotechnology, which are generic advanced technologies that have a wide application across different industries (OECD 2013). The high technology ISIC sectors include the defense sector, which is a special case due to its close government links and national security role. The defense industry has also been an important driver of technological advancement, including in communications technology and aviation (Chakrabarti and Dror 1994). The defense sector combines ISIC groups 252 (Manufacture of weapons and ammunition) and 304 (Manufacture of military fighting vehicles). ISIC sector-related patents are identified based on the concordance tables of Lybbert and Zolas (2014). Table A.1 (appendix A.2) shows a summary of the ISIC or CPC identification classes for the reference sectors. Note that there is some overlap in patents between the Medical Life Sciences and Biotechnology sectors: the majority of Medical Life Science patents are also included in the more broadly defined Biotechnology sector.

Table 4.3: Sustainability technology sectors with their respective ISIC or CPC identification classes.

Sector Name	**Identification classes**
Medical Devices	ISIC group 266 and 325
Medical Life Sciences	CPC classes C07K, C07H 21, C12N, A61K 35, 38, 39 and 3171.
Biofuels	CPC class Y02E 50/10
Electric vehicles	CPC class Y02T 10/64, 10/70 and 10/72
Energy storage	CPC class Y02E 60/10
Fuel cells	CPC class Y02E 60/50
Hydrogen technology	CPC class Y02E 60/30
Photovoltaics	CPC class Y02E 10/50
Wind turbines	CPC class Y02E 10/70

4.5 Cluster Identification Methodology Parameter Calibration

The “heat map” cluster identification algorithm used in this study requires the calibration of an interpolation range (R) and concentration threshold (T) parameter, a process described in subsection 4.5.1. These parameters, which are calibrated using a complete patent data set (all sectors), are subsequently applied to the respective sectors in order to evaluate their performance (subsection 4.5.2) . The calibration exercise is based on three criteria: maximum cluster size, performance of the clustering algorithm and the number of clusters (ensuring small clusters are also detected). The sensitivity analysis is carried out by varying the interpolation range and concentration threshold using values that seem reasonable based on the literature, and which clearly show an optimum (at least one value lower and one value higher). A total of four different values is explored for each parameter, leading to 16 possible combinations, of which one is optimal (interpolation range $R = 25$ km, concentration threshold $T = 97.5\%$).

4.5.1 Calibration and Sensitivity Analysis

The “heat map” approach is formally known as the Kernel Density Estimation (KDE) method (Rosenblatt 1956; Parzen 1962; Davies, Marshall, and Hazelton 2018), a spatial interpolation technique frequently used to spatially compile data about phenomena such as crime levels, traffic accidents, property values as well as temperature, from which the “heat map”-terminology originates. Areas with frequent occurrences, high prices or high temperatures are assigned high values on the heat map, and can be identified as “hot spots.” Areas with a high patent density (“hot spots”) are identified as clusters. In this study the heat map KDE is carried out on a raster with squares of 5 km by 5 km covering the entire world.

When applying the KDE method to identify clusters, decisions must be made about two important variables: the interpolation range (R) and the concentration threshold (T). The interpolation range describes the distance at which different inventors are still part of the same cluster. The interpolation range can be decided based on several criteria, for example Van Egeraat et al. (2018) uses commuting distance while Alcácer and Zhao (2016) uses 20 mi (32 km, without any justification given). Acs, Anselin, and Varga (2002) notes that within a 50 mi (80.5 km) distance from the boundaries of a metropolitan statistical area, there is still some positive innovation effect. The distance cited by Acs, Anselin, and Varga (2002) is about four times the largest average daily commuting distance of a US city (Atlanta, GA, average commuting distance of 20.6 km) (Kneebone and Holmes 2015). Due to this variation, the cluster interpolation range is calibrated using sensitivity analysis (see table 4.6). In a similar way there is also no strong theoretical bases for establishing the concentration threshold (T) and therefore a sensitivity analysis is also applied to calibrate this parameter.

In this study the parameter calibration (sensitivity analysis) is subject to three conditions/goals:

(i) the maximum cluster size (A_{max}) should not exceed the size of a major urban area. Very large clusters suggest that the interpolation distance is too great or the threshold value is too low “sticking” multiple urban areas together. This situation can occur in urbanized and R&D intensive parts of the world such as Western Europe, New England, South Korea and

Japan where giant "clusters" that encompass whole or even multiple countries can appear. To gain an idea of a "reasonable" metropolitan area size, see the areas of selected large metropolitan areas in table 4.4.

(ii) to measure the performance (quality) of the cluster identification algorithm, patent co-inventors close together should be identified as being in the same cluster whereas those located further apart should be identified as being in different clusters. In their paper on identifying clusters from patent data, Alcácer and Zhao (2016) calculate the share of patents with co-inventors located 16-32 km apart within the *same* cluster (D_{same}) and the share of patents with co-inventors located more than 32 km and located in *different* clusters (D_{dif}). A high value for both indicators suggests the cluster spatial distribution in question is of high quality. The values for D_{same} and D_{dif} calculated by Alcácer and Zhao (2016) are listed in table 4.5. The table includes values for two types of "organic" clustering algorithms developed by Alcácer and Zhao (2016).

(iii) the number of clusters (n) identified is an important criterion to evaluate the cluster spatial distribution because a method that identifies only a small number of clusters is likely blind to many smaller and emerging clusters.

The parameter calibration is carried out using patent data for all sectors for the 2008-2011 period with the patent output correction factor (COR_{PAT}) applied to all inventor locations outside the United States. Different parameter values produce 16 different cluster identification results, which can be evaluated based on the criteria stated above. To provide references for their evaluation, examples of maximum cluster area size (A_{max}) are shown in table 4.4. These maximum cluster areas are based on the largest metropolitan areas of several countries. They include the Île-de-France and South East England regions surrounding Paris and London, the New York-Newark-Jersey City metropolitan statistical area (MSA), Greater Tokyo and the Pearl River Delta. These regions are all identified as the largest metropolitan areas by their respective national governments. Bergquist, Fink, and Raffo (2017) also views the Pearl River Delta, which includes Guangzhou, Shenzhen and Hong Kong, as a single cluster, although the United Nations Population Division lists these three cities as separate urban agglomerations (United Nations Population Division 2018). Benchmark values for the quality of the cluster identification results are shown in table 4.5. The benchmark values include both pre-determined cluster boundaries and cluster boundaries from organic clustering algorithms developed by Alcácer and Zhao (2016). The complete results of the cluster identification sensitivity analysis are shown in table 4.6.

Table 4.4: Selected examples of large metropolitan areas (source: national government statistics).

Country	**Metropolitan Area**	**Main City**	**Size (km^2)**
France	Île-de-France	Paris	12,012
Japan	Greater Tokyo Area	Tokyo	14,034
UK	South East England	London	19,096
USA	New York-Newark-Jersey City, NY-NJ-PA	New York	37,303
China	Pearl River Delta	Guangzhou	39,380

Table 4.5: Performance of different cluster identification methods based on percentage same (D_{same}) or different cluster co-inventors at 32 km (D_{dif}).

Boundaries	**Type**	D_{same}	D_{dif}
US State	Pre-determined	98%	47%
US Economic Area	Pre-determined	100%	48%
US Metropolitan Statistical Area	Pre-determined	97%	46%
US County	Pre-determined	74%	90%
Country (excl. US)	Pre-determined	100%	22%
Organic Clustering (world)	Organic	100%	59%
Hierarchical Clustering (world)	Organic	100%	50%

Note: From Alcácer and Zhao (2016).

Table 4.6: Cluster identification sensitivity analysis based on interpolation distance (R) and concentration threshold (T).

Distance / Threshold	T = **90%**	T = **95%**	T = **97.5%**	T = **99%**
R = **15 km**	A_{max} = 65,389 D_{same} = 97% D_{dif} = 67% n = 1,410	A_{max} = 33,953 D_{same} = 94% D_{dif} = 70% n = 841	A_{max} = 17,914 D_{same} = 92% D_{dif} = 73% n = 492	A_{max} = 6,070 D_{same} = 82% D_{dif} = 77% n = 252
R = **25 km**	A_{max} = 162,334 D_{same} = 100% D_{dif} = 56% n = 949	A_{max} = 59,408 D_{same} = 99% D_{dif} = 62% n = 489	A_{max} = 32,972 D_{same} = 99% D_{dif} = 66% n = 355	A_{max} = 9,505 D_{same} = 99% D_{dif} = 67% n = 169
R = **32 km**	A_{max} = 451,689 D_{same} = 100% D_{dif} = 50% n = 508	A_{max} = 144,415 D_{same} = 100% D_{dif} = 54% n = 334	A_{max} = 51,345 D_{same} = 100% D_{dif} = 56% n = 206	A_{max} = 23,479 D_{same} = 100% D_{dif} = 59% n = 108
R = **50 km**	A_{max} = 623,172 D_{same} = 100% D_{dif} = 46% n = 371	A_{max} = 319,188 D_{same} = 100% D_{dif} = 48% n = 251	A_{max} = 100,697 D_{same} = 100% D_{dif} = 51% n = 157	A_{max} = 45,413 D_{same} = 100% D_{dif} = 49% n = 87

The sensitivity analysis results (table 4.6) are now assessed based on the aforementioned three criteria: maximum cluster size, cluster algorithm performance and the number of clusters. Assessing the sensitivity analysis results based on the largest cluster area (A_{max}), shows that when $T = 90\%$ or $R = 50$ km very large cluster areas are identified which exceed the size of typical major urban areas (table 4.4). The smallest value for A_{max} = 45,413 km^2 ($R = 50$ km, $T = 99\%$) is larger than the urban areas centered on New York and Guangzhou. Other distance-threshold combinations also show A_{max} values that seem excessively large, including $R = 25$ km with $T = 95\%$, and

R = 32 km and T = 97.5%. At these combinations of interpolation distance and concentration thresholds unrealistically large technology clusters are identified.

Assessing the results based on the second criterion, the performance of the cluster identification algorithm, reveals an interesting trend: results where R = 25 or 15 km have a less than 100% value for D_{same}, suggesting that some of the identified clusters are "too small" as inventors located nearby fall outside the cluster boundaries. The combinations with the highest cumulative cluster performance value ($D_{same} + D_{dif}$) and a D_{same} value of at least 99% are R = 25 km and T = 97.5% or 99%, with a cumulative cluster performance value of 165% and 166%, respectively.

Based on the third criterion, in the two aforementioned cluster distributions, T = 97.5% yields a significantly larger number of clusters (n = 355) than the T = 99% alternative (n = 169). If more clusters are identified more smaller clusters are included. Therefore, the former (R = 25 km, T = 97.5%) is considered as the optimum heat map cluster identification algorithm based on global data for the 2008-2011 period. The smallest technology clusters identified using the optimum heat map algorithm are 50 km^2 in size. The largest clusters are centered on New York City (32,972 km^2), Tokyo (15,941 km^2), Los Angeles (12,723 km^2) and San Francisco (11,733 km^2).

A more detailed discussion of the cluster identification results, including a sample "heat map" image of patent concentrations is presented in appendix A.3.

4.5.2 Evaluation of Parameters for Multiple Sectors

Having calibrated the heat map cluster identification method with the most suitable interpolation range (R) and threshold concentration (T), the same methodology (with the same parameters) is now applied to different sectors to evaluate the suitability of its use. Because the cluster identification method is largely automated, it becomes possible to quickly identify sectoral clusters, and to do so on a global scale. An overview of the key cluster indicators for each sector are provided in table 4.7. In addition to the maximum cluster area (A_{max}), the share of co-inventors located 16-32 km apart within the *same* cluster (D_{same}) and the share of patents with co-inventors located more than 32 km and located in *different* clusters (D_{dif}), the total number of patents from the sector (P_{total}) and the share of patents located in clusters ($PS_{cluster}$) are also shown.

The cluster identification performance results (table 4.7) show notable variations between sectors, which follow a relatively consistent pattern. To interpret the results, it should be noted that a lower same-cluster D_{same} value suggests that the clusters of that sector are less dense (lower spatial concentration), because inventors who are relatively close to each other are not identified as being in the same cluster. A lower different-cluster D_{dif} value suggests that clusters can be very large, because inventors who are relatively far apart are still found in the same cluster. A higher D_{dif} value suggests that clusters are relatively small, because inventors who are far apart are almost always in different clusters.

Most sectors broadly follow the clustering performance measures obtained during the calibration, especially for the same-cluster D_{same} value. The lowest same-cluster D_{same} values are found in Defense (90%) and Biotechnology (89%). These sectors also have a low clustering rate (Defense 34%, Biotechnology 25%), however not all sectors with low clustering rates have low same-cluster D_{same} values. The sectors with very high different-cluster D_{dif} values tend to have small clusters. This is evident from Wind turbines (A_{max} = 2,014 km^2, D_{dif} = 98%), Hydrogen technology (A_{max} = 2,570 km^2, D_{dif} = 86%) and Biotechnology (A_{max} = 3,542 km^2, D_{dif} = 90%). However, not all sectors with a small maximum cluster size have high different-cluster D_{dif} values, as is evident from Defense, Medical devices and Energy storage. The sectors that closely follow the average in terms of same-cluster D_{same} and different-cluster D_{dif} values are the large reference high technology sectors such as Chemicals, Computers and Electrical equipment, which can have very large clusters and typically have a high share of patents located inside clusters. In addition to table 4.7, an overview of clustering indicators for all sectors included in this study is also shown in table A.2 of appendix A.4.

Table 4.7: Clustering indicators for selected sectors.

Sector	A_{max}	D_{same}	D_{dif}	n	P_{total}	$PS_{cluster}$
Chemicals	26,539 km^2	100%	61%	168	140,255	75%
Computer and electronics	19,964 km^2	100%	63%	154	527,516	85%
Defense	3,542 km^2	90%	65%	55	4,790	34%
Electrical equipment	16,074 km^2	99%	63%	143	92,310	73%
Biotechnology	3,542 km^2	89%	90%	57	26,981	25%
Medical devices	3,542 km^2	100%	60%	71	39,948	25%
Energy storage	3,917 km^2	99%	51%	17	2,847	26%
Hydrogen technology	2,570 km^2	98%	86%	14	954	25%
Wind turbines	2,014 km^2	96%	98%	24	2,775	31%

Rather than suggesting that the cluster identification methodology is inaccurate for certain sectors, the results suggests that there are notable differences in the spatial distribution of different sectors, including the share of patents found in clusters and the maximum cluster size. These differences suggest that the patenting patterns of these sectors, and thus the spatial dimension of their innovation process, show notable differences. Some of the possible causes of these sectoral differences are further addressed in later chapters. Having noted these sectoral differences, an alternative approach could be to calibrate the clustering algorithm parameters separately for different sectors. However, this approach might complicate sectoral comparisons because in terms of how clusters are identified would differ. Hence a uniform approach appears most suitable given the research goals of this study.

4.6 Summary and Discussion

The cluster identification methodology presented in this chapter is based on the design criteria formulated in section 4.3. These design criteria include: the use of a single source of patent data, analyzing single industries or sectors, identifying realistic clusters (imposing a maximum cluster size), the performance (low errors) of the clustering algorithm and its ease of use for policy makers and stakeholders. The cluster identification methodology satisfies these criteria, and they are discussed in this section with occasional references to other cluster identification methodologies.

The use of a single source of patent data ensures a uniform standard of patent evaluation worldwide and removes the biases caused by different patent offices maintaining different evaluation standards (Laurens et al. 2015; Toivanen and Suominen 2015). In this study the United States Patent and Trademark Office (USPTO) database is used as a single patent source and a home bias correction is carried out. The home bias correction is based on the assumption that Japan is most similar to the United States in terms of its technological profile (Mancusi 2008; Toivanen and Suominen 2015). A correction factor is calculated based on the differences in patenting and citation frequencies between Japanese and American inventors at the USPTO. The advantage of this approach is its simplicity and transparency. Its drawback is that other factors, such as economic and trade relations, are also seen to influence patenting at foreign patent offices (Yang and Kuo 2008), something not taken into account in this study. Furthermore, instead of choosing a single country (Japan), a group of advanced economies could have been used as reference countries. While these are valid considerations, it must be noted that the use of the correction factor is limited in the study to specific indicators. It is applied when making comparisons between the size of clusters (patent counts) and calculating innovation performance (citation counts), but not when studying knowledge networks or the actor composition of a cluster (see section 3.5). Therefore, a significant part of the study results are not influenced by the correction factor, while the simplicity of the correction factor makes it easy to understand its influence when interpreting the other results.

A related concern about different patenting frequencies and citations are sectoral differences (Kleinknecht, Van Montfort, and Brouwer 2002; Hall, Jaffe, and Trajtenberg 2005). In this study clusters are identified for each sector, although the calibration of clustering algorithm parameters is done using all patents (covering all sectors). This approach provides a uniform criterion for identifying clusters while ensuring that sectors with low patenting frequencies are not submerged by sectors with high patenting propensities.

If patents from multiple patent offices had been used, and all sectors had been combined, one would expect an inflation of patent counts for: (i) clusters located in countries such as China, South Korea and Japan, where the threshold for granting patents tends to be lower, see: Laurens et al. (2015), and (ii) clusters with a strong focus on pharmaceuticals, life sciences and electronics, which are known to produce many patents relative to R&D expenditure. This is precisely the result obtained by Bergquist, Fink, and Raffo (2017), who identify clusters using the Patent Cooperation Treaty (PCT) database of the World Intellectual Property Organization (WIPO). Among the 10 largest clusters, 6 are found in Asia and 8 have electronics or pharmaceuticals as their top area of invention. In the Netherlands the electronics cluster of Eindhoven (#18) ranks far higher than the more machinery- and chemicals-focused clusters of Rotterdam-The Hague (#45) and Amsterdam (#91). These results show that the decision to use a single patent source and to carefully consider the role of sectors, is non-trivial.

In addition to avoiding measurement biases, the cluster identification methodology has also been optimized by aiming to identify as many clusters as possible (ensuring the detection of smaller clusters), and by imposing a maximum cluster size, to ensure realistic clusters are identified (Han et al. 2016; Ma et al. 2016). These conditions have ensured a clustering algorithm that performs significantly better than methodologies using predefined cluster boundaries, while reaching, or in some respects slightly exceeding, the performance of the organic clustering algorithm developed by Alcácer and Zhao (2016).

A further point to emphasize is that the cluster identification method used in this study is automated and standardized. For example, no adjustments are made for commuting distances in densely populated areas (Van Egeraat et al. 2018), nor are significant manual interventions undertaken to locate patents (Alcácer and Zhao 2016). Instead a single patent frequency correction factor is calculated to address the home bias effect and the generation of heat maps and calculation of concentration thresholds is standardized. While there may be some inaccuracies due to automation, the benefit of automation is that multiple sectors and time periods can be analyzed quickly, and the method is therefore also very suitable for comparative studies, longitudinal studies or "real time" monitoring of innovation performance, for example by policy makers. To illustrate the difference in scale between two studies: Alcácer and Zhao (2016) used 23,675 unique patents, whereas the present study used 1,216,004 unique patents to identify clusters, 51 times more. A simpler but reasonably accurate cluster identification tool such as the one developed in this study can support policy making and decision-making by other stakeholders. This makes the methodology suitable for the monitoring of cluster development, for example by countries wishing to evaluate their cluster policy and innovation performance, or by the European Commission, which as part of its Horizon 2020 goals includes smart and inclusive innovation of regions.

A final question concerning the performance of the clustering algorithm is its level of uncertainty, which is of great importance when interpreting results based on the identified clusters. Uncertainty is difficult to calculate in this case because there is no "true" global data set of clusters with which the heatmap results can be compared. For this reason the focus of the analysis in later chapters is on identifying trends, regression analysis and statistical analysis of differences (e.g. student t-test), which should be robust to the uncertainty that comes with identifying technology clusters from patent data.

In conclusion, the methodology has met the design criteria set out at the beginning of this chapter. Its high level of automation suggests that it can be widely applied, both in research and in the real-time monitoring of spatial innovation patterns worldwide and across multiple sectors.

Chapter 5

Health Technology Clusters

5.1 Introduction

The health technology sector plays an important role in addressing the challenges of ageing populations and the related increased demand for medical care (partly due to an increase in chronic diseases) and the need to reduce the cost of healthcare (European Commission 2010, 2014b, 2018; World Health Organization 2019). In this study, the health technology sector is defined based on two technological sub-sectors: medical devices and medical life sciences. This chapter provides a descriptive analysis of the spatial distribution, agglomeration, and knowledge networks of health technology clusters, and an explanatory analysis of their innovation performance.

The chapter begins with a profile of the health technology sector and its two sub-sectors (section 5.2). This profile includes a characterization of the sector's growth trajectory, knowledge base, innovation actors, and technological and market trends. These factors, among others, influence the sector's spatial distribution and shifts therein, and agglomeration and knowledge network structure and change, which are described in section 5.3. The description covers a 12-year period, from 2000 to 2011, allowing changes (if any) to be observed, including changes in the location and growth of clusters in the context of "global shifts" (Dicken 2007). The spatial analysis is further extended by exploring the largest, newly emerged and fast-growing health technology clusters during the 2000-2011 study period, providing insight into spatial changes at the level of individual clusters. Next, the characteristics associated with cluster innovation performance are analyzed using a regression model (section 5.4). The model is used to evaluate the statistical significance of the association between cluster innovation performance and agglomeration, national innovation system, knowledge networks, and path dependence. The model and model indicators are described in detail in chapter 3 (Data and Methodology). Section 5.5 covers the evaluation of the hypotheses, a discussion of the knowledge gaps and the chapter's empirical results. The conclusion of the chapter (section 5.6) gives an overview of the main research findings, together with their theoretical and policy implications, and remaining research questions.

5.2 Sector Profile

The sector profile gives an overview of the two health technology sub-sectors: medical devices and medical life sciences. The sector profile includes the growth trajectories of the sub-sectors patent output during the 2000-2011 period (subsection 5.2.1), an overview of the sub-sectors' knowledge base and recent technological trends (subsection 5.2.2), and a discussion of the main innovation actors and the relative size of the sub-sectors (subsection 5.2.3). The knowledge base and the institutional landscape are seen as important factors that influence sector and cluster innovation activity (Breschi and Malerba 1997; Iammarino and McCann 2006). The analysis confirms the characterization of the health technology sector as a mature sector and shows clear differences between the two sub-sectors, which can be attributed to their knowledge base.

5.2.1 Sector Growth

The aggregate health technology sector has experienced strong growth in recent decades, although this growth has not been constant, and there are important differences in growth trajectories between the medical life sciences and medical devices sub-sectors. Globally, demand for healthcare is rising as people live longer and incomes gradually rise, both in the developed and developing world (Deloitte 2016; OECD 2017). Rising incomes are leading not just to more consumer spending but also to rising medical insurance, both through public and private schemes, which also raise healthcare expenditure (Deloitte 2016). A second trend is the demographic shift towards ageing populations as taking place in advanced economies such as Europe and Japan, but also in emerging economies such as Argentina, Thailand, and China. Ageing leads to an increasing prevalence of chronic diseases which increase demand for medical care (Deloitte 2016; OECD 2017). While demand is rising, there is also pressure to innovate, because innovation is expected to contribute to the provision of better healthcare at lower cost, for example through digitization. This is important to ensure the affordability and accessibility of healthcare, especially in ageing societies whose demand for healthcare is increasing while economic growth tends to decline due to a shrinking working age population (OECD 2017; World Health Organisation 2017).

Investment in healthcare research and innovation is also affected by increasing regulatory approval requirements and government scrutiny, which is increasing the cost of bringing innovations to market (Hall and Wood 2008; McNamee and Ledley 2012; OECD 2017). Insurance companies and governments also play an economic regulatory role, as they make decisions about insurance coverage for new treatments, and sometimes negotiate pricing and supply directly with producers (PwC Health Research Institute 2013).

The health technology sector has strong drivers for growth and innovation as explained above, however the two sub-sectors show very different growth and innovation patterns. The medical life sciences sector is a high-risk and high-reward sector, making it an attractive investment target for venture capital. As venture capital is a major source of medical life sciences research funding, its volatility influences the innovation activity of the sector (Booth 2016). The volatility is evident from the number of medical life science patents, which after 2001 faces a steep decline following the so-called "dot com" internet bubble (see Booth (2016) and figure 5.1, below), only recovering after 2005. This is in contrast to the medical devices sector which is generally seen as a more stable sector, which delivers consistent and relatively high growth (MedTech Europe 2016). This stable growth trajectory is also evident from its patent output, see figure 5.1.

During the 2000-2011 study period, the number of medical life sciences patents experienced significant fluctuations, with a high of 7,064 in 2000 and a low of 5,015 in 2005, before rising back to 6,865 in 2011. The number of medical device patents rose from 7,353 to 10,928 during the same period, an increase of 49% over 12 years. Being among the most prolific of all technology sectors in terms of patent output, the knowledge output of the medical devices sector appears to be relatively large (European Patent Office 2014). In reality, the estimated R&D expenditure at the end of the study period was US$270 billion per year for medical life sciences (government and private sector), far more than the US$15 billion per year in medical devices R&D expenditure (private sector only) (Ernst & Young 2012; Chakma et al. 2014). The relatively modest or negative growth rate of the health technology sub-sectors suggests that both sub-sectors were in a mature and path dependent development phase, with the medical devices sector recording stable growth, while the medical life sciences sector experienced a boom-and-bust cycle (Martin and Simmie 2008; Booth 2016).

Despite its moderate growth levels, health technology is viewed as an attractive industry sector and is promoted by countries and cities because it creates high income employment. Countries such as Australia, China, Japan, Russia, Singapore, and South Africa have all introduced legislation to attract medical research by offering tax incentives, facilitating international clinical trials, and making foreign research projects eligible for public research grants. Switzerland and the United Kingdom are the two leading countries in attracting international medical research funds (Deloitte 2016).

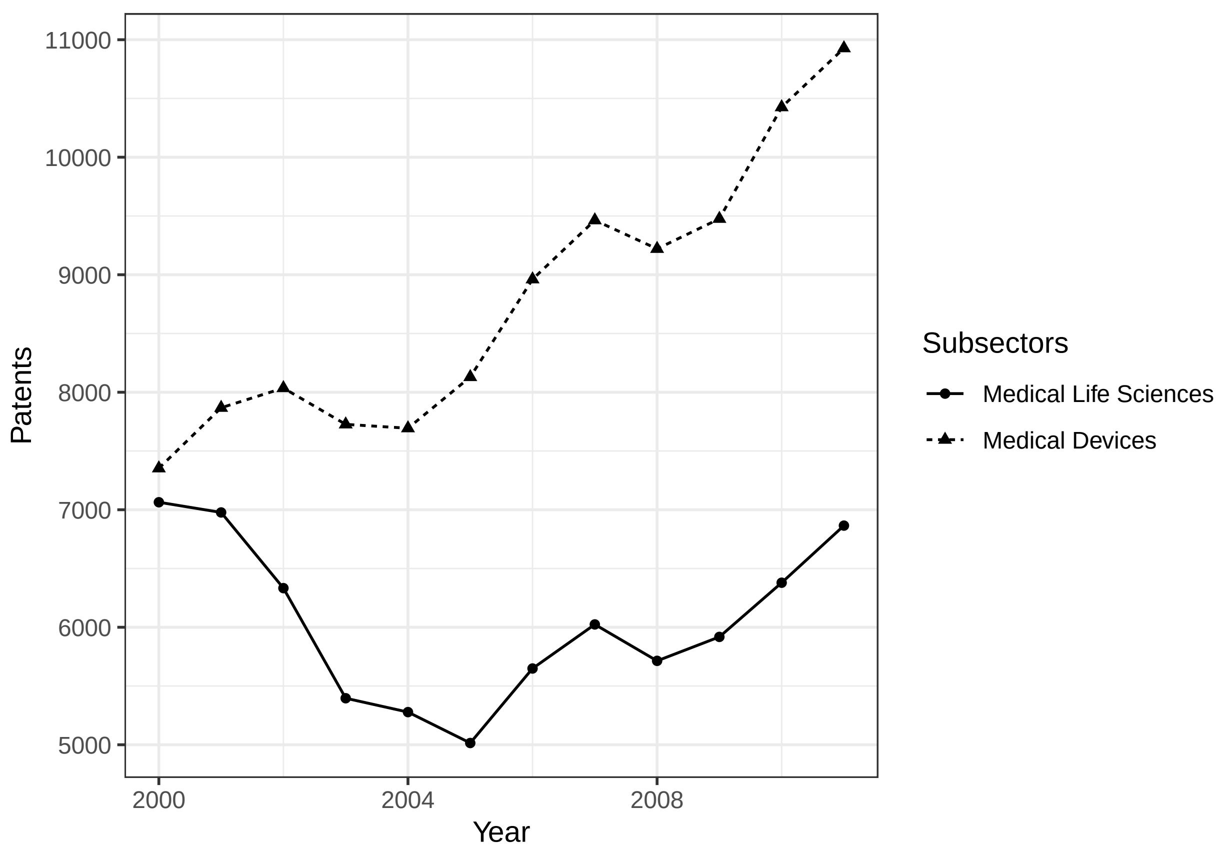

Figure 5.1: Annual health technology patent grants by sub-sectors based on application year (source: USPTO).

5.2.2 Sectoral Knowledge Base and Technological Trends

The sectoral knowledge base and technological trends are important influences in the innovation process of every sector, making them important background conditions for an analysis of different (sub)sectors. The knowledge base is important because it influences which institutions participate in cluster innovation activity and the extent to which collaboration with universities and public research institutions is likely to take place. (Asheim and Coenen 2005; Tidd, Bessant, and Pavitt 2005; Carlsson 2013) In sectors with a scientific knowledge base, basic (fundamental) research is an important source of innovation. As a result, collaboration by industry with universities and public research institutions tends to occur more frequently. Knowledge also tends to be more codified, facilitating collaboration over long distances (Asheim and Coenen 2005; Carlsson 2013). Sectors with an engineering and design knowledge base innovate based on close interactions with customers and suppliers, and through "learning by doing," enabling the local accumulation of experience and specialized skills (Jeannerat and Kebir 2016).

When distinguishing between the medical life sciences and medical devices, the first sub-sector is seen as having a more scientific knowledge base, whereas medical devices appears to have an engineering and design knowledge base (Tidd 2001; Gilsing et al. 2011; Binz and Truffer 2017). Medical life sciences involves the study of living organisms with medical and pharmaceutical applications, sometimes referred to as "biologics" in the pharmaceutical industry. Within the scope of biologics are peptides, antibodies and antigens, nucleic acid based therapeutics and enzymes (IP Australia 2015). Another growing area of medical life sciences research is genetic engineering, including gene therapies (Mentesana et al. 2017). Medical life sciences research is closely connected to the scientific research taking place at universities and public research institutions, and medical life sciences firms frequently collaborate, or fund contract research, at universities and public research institutions (Blumenthal et al. 1996; Owen-Smith et al. 2002).

The medical devices sector includes the production of radiotherapeutic and electrotherapeutic equipment, which is closely connected to the electronics industry, and the production of medical (including surgical) and dental instruments (United Nations Statistical Division 2008). Products that fall within the scope of the medical devices industry include CT scanners, PET scanners, magnetic resonance imaging (MRI) equipment, medical ultrasound equipment, electrocardiographs, electromedical endoscopic equipment, medical laser equipment, pacemakers and hearing aids, and also bone and tooth implants and reconstruction cements, ultrasonic cleaning machinery, sterilizers, medical laboratory equipment, bone plates, screws, syringes, needles, catheters, orthopedic devices, prosthetic devices and ophthalmic goods (eye glasses and related) (United Nations Statistical Division 2008). Medical device innovation activity is seen as being multidisciplinary, integrating advances in basic research from physics, material sciences, mathematics and engineering (Gelijns and Thier 2002). Innovations are often pioneered in collaboration between firms and academic hospitals (Gelijns and Thier 2002). Tidd (2001) classifies medical instruments as a specialized supplier sector, which is grouped as a kind of engineering-based sector. Based on these descriptions from the professional and academic literature, medical devices can be seen as being a more engineering-based sector than the medical life sciences.

The scientific knowledge base of the medical life science sector means that innovation trends closely follow scientific discoveries in the field (Blumenthal et al. 1996; Gelijns and Thier 2002; Owen-Smith et al. 2002). On the other hand the medical devices sector or "medtech" (PwC Health Research Institute 2013; MedTech Europe 2016) is influenced by multiple and broad-based technological and scientific trends. These trends include miniaturization, the falling cost of electrical components and the creation of new materials. These trends are part of a broader trend of interdisciplinary high technology research, so-called "technological convergence," is also taking place in other areas of science (Chen 2009). Miniaturization, which is reaching nano-scales, enables the integration of multiple functions into a single device. The falling cost of many electrical components enables the expanded connectivity of devices, enabling better and automated monitoring of patients and drug delivery. The integration of new biomaterials in medical devices promises to improve biology-machine interactions, opening up novel applications such as bioimplants (Chen 2009; Deloitte 2016; Mentesana et al. 2017). Finally, two technology trends in clinical surgery need to be mentioned, namely, minimal invasive surgery and robotic-assisted surgery, calling for new surgical equipment, steering equipment, and digitization (algorithms).

The trend of technological convergence also affects the medical life sciences, and the falling cost of genome sequencing is especially significant. Affordable sequencing of an individual's genome enables the personalization of medicine, which can increase the effectiveness of medical treatment while reducing costs by avoiding ineffective or unnecessary treatments (Mentesana et al. 2017). Aside from personalization, a deeper understanding of genetics in general has made possible the discovery of new medical life science drugs ('biologics') which tend to be more targeted, more effective and have fewer side-effects than conventional treatments. A deeper understanding of genetics also makes it possible to better predict the behavior of treatments in real-world conditions (Škalko-Basnet 2014; Lybecker 2016; Mentesana et al. 2017). The advance of biologics has a profound impact on the pharmaceuticals industry as "broad" conventional medicines are being replaced with "niche" biologics, changing the drug development and sales process (Škalko-Basnet 2014; Lybecker 2016). Biologics also present challenges in terms of drug delivery systems and production processes, both of which are extremely sensitive and require higher levels of monitoring and quality control, creating an important avenue for future research (Škalko-Basnet 2014; Lybecker 2016).

5.2.3 Innovation Actors

The differences in the sectoral knowledge base of the health technology sub-sectors is also evident from an analysis of the main innovation actors. The classification of medical life sciences as a sector with a scientific knowledge base and medical devices as a sector with an engineering and design knowledge base, appears to be supported by a greater participation of public research institutions, and especially universities, in the medical life sciences sector. In the medical life sciences sector universities account for 21% of innovation activity (measured by patents) and government for 2%. In the medical devices sector these shares are lower at 5% and 1% respectively (see table D.1, appendix D.1).

The greater role of universities and government in medical life sciences is also seen in the list of top 10 innovation actors worldwide (measured by patents). The University of California and the U.S. Department of Health and Human Services take second and fifth place, respectively (see table D.1, appendix D.1).

The notable difference in sub-sector size should be taken into account when interpreting the aggregate health technology results of this study. In the descriptive spatial analysis (section 5.3) the aggregate number of health technology *patents* is used, and approximately 31% of patents are from the medical life sciences sub-sector and 69% are from the medical devices sub-sector, suggesting skewed results towards the latter (2008-2011, see also table D.2, appendix D.1). However, for parts of the spatial, agglomeration and knowledge network analysis and for the cluster innovation performance model the aggregate number of health technology *clusters* is used. Medical life sciences clusters (146 or 67%) are larger in number than medical devices clusters (73 or 33%, 2008-2011 see also table D.2, appendix D.1). Since most of the analysis takes place at the cluster level and the medical life sciences sub-sector has a larger number of clusters, the analysis of the health technology sector is mostly skewed towards the medical life sciences sub-sector. A stronger presence of the medical life sciences in the analysis coincides with the larger amount of R&D expenditure in the sub-sector (Chakma et al. 2014). Therefore, this unbalanced situation is considered acceptable and no adjustments to sub-sector weightings are made.

5.3 Cluster Characteristics and Spatial Distribution

This section provides insight into the spatial distribution, agglomeration and knowledge network characteristics of health technology clusters. The section is divided into two parts. The first part describes clusters, agglomeration (subsection 5.3.1), and knowledge networks (subsection 5.3.2) using descriptive statistics. The second part describes the spatial distribution of the largest technology clusters, and identifies fastest-growing, fastest-declining, and newly emerging health technology clusters (subsection 5.3.3).

5.3.1 Clusters and Agglomeration

Spatial concentration brings about agglomeration economies favorable for R&D and other types of learning. Spatial concentration lowers transport and communication costs, can increase the quality of services and labor market supply, and can facilitate knowledge spillovers. However, there seems to be an inflection point of city- or cluster-size at which agglomeration economies turn into diseconomies.

Table 5.1 provides statistics for three four-year periods from 2000-2011 for the aggregate health technology sector. The statistics are subdivided by the *Clusters and Agglomeration* and *Knowledge Networks* headings. The Cluster and Agglomeration indicators are derived from patent counts. Patent counts are a measure of innovation activity and the location of patent inventors and their institutional affiliation provides an indication of where innovation activity takes place and by which institutions (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004; Squicciarini, Dernis, and Criscuolo 2013). Health technology patents are identified using a set of International/Cooperative Patent Classification (CPC/IPC) codes which were also used in earlier bibliometric research on the medical life sciences and medical devices (IP Australia 2014, 2015). Patent counts are corrected for the home bias effect (for details, see chapter 4).

The total number of health technology patents shows some small fluctuations during the 2000-2011 period, with a low of 65,519 in 2004-2007 and a high of 72,051 in 2008-2011.[1] The distribution of patent output across continents is generally stable. Europe's share has declined slightly from 24% to 22% during the 2000-2011 period while Asia's share has increased slightly from 19% to 22%. The share of North America and the Rest of the World has stayed constant at 53-54% and

[1]Note that the number of patents reported in table 5.1 and section 5.2 is slightly different. This is because the numbers in table 5.1 were corrected for the home bias effect, which increases the weighting of non-United States patents (see chapter 4 for details).

2% respectively. Although there is a small increase in Asia's share of health technology innovation activity, it does not appear to be a large shift (hypothesis 1).

Along with the fluctuation in the number of patents, the number of health technology clusters has also varied slightly during the study period, from a low of 214 (2004-2007) to a high of 219 (2008-2011). The global distribution of clusters has remained almost constant. North America accounts for 60-61%, Europe for 21-22%, Asia for 15% the Rest of the World 3%.

Also relatively unchanged are the 133.2-149.8 patents per cluster and the cluster size Gini coefficient is 0.66-0.67, suggesting there are no big changes in agglomeration in the health technology sector. There is a decline in the share of clustered patents from 47% to 42%, which is presumably related to the growth of the medical devices sub-sector, which has a lower clustering rate (see table C.3, appendix C.2). The medical devices sub-sector has a clustering rate of just 24%. The clustering rate of the medical life sciences sub-sector is 72%. Such a large difference in clustering rates between the sub-sectors is unexpected because both are in a mature development phase, which is typically associated with a higher degree of clustering (Crescenzi and Rodríguez-Pose 2011; Frenken, Cefis, and Stam 2015). A possible explanation for this phenomenon, at least in Europe, is that the medical devices sub-sector partially developed in smaller cities several decades ago. For example, in Nuernberg and Erlangen (Germany) the precursor of Siemens Healthcare was established, and Siemens' headquarters have remained there. In addition, the concentration of firms in small towns like in the Alsace and Franche-Comte regions (France), originated from traditional fine-mechanics and watchmaking industries here. By contrast, Galway (Ireland) can be seen as a late-coming cluster created as a result of a policy of investment promotion since the early 1970s. It first attracted manufacturing activities through foreign direct investment, but later it moved up in the value chain towards high level R&D (Klein, Banga, and Martelli 2015).

In addition, the application of multiple and sometimes more broad-based technologies in medical device innovations (Chen 2009) could mean that collaboration with organizations from other sectors (e.g. micro-electronics, imaging, etc.) is more frequent, reducing the importance of large "pure" medical device clusters. Medical life science research on the other hand may be more spatially concentrated because it is anchored around universities due to the importance of basic scientific research (Casper 2013).

The role of universities and public research institutions varies significantly between the sectors. The medical devices sub-sector has a notably higher corporate patenting share (88.3%) as compared to the medical life sciences sub-sector (65.9%). A lower corporate patenting share suggests a greater role in healthcare R&D by universities and public research institutions.

In addition to the aforementioned sub-sector differences, there are also two notable differences in the continental distribution of patent output and clusters. First, the medical devices sector is concentrated in North America (53% of patent output), followed by Asia (25%), and Europe (21%). However, the medical life sciences sector is concentrated in North America (61%), followed by Europe (25%), and then Asia (17%). Asia thus has a higher share of medical device patents compared to medical life sciences, while Europe is stronger in medical life sciences, with North America accounting for the largest share in both sub-sectors. The second difference are continent-level variations between patent output and the number of clusters. This difference is especially pronounced in the medical devices sector: North America has 53% of medical devices patents but a much larger 84% of clusters, whereas Europe's 21% patent share is linked to just 3 clusters (4%), and Asia's 25% patent share is linked to only 9 clusters (12%). Asia has a number of large medical device clusters such as Tokyo, Seoul, Tel Aviv, and Taipei (see also table C.4, appendix C.2), and therefore Asia appears to have a more spatially concentrated medical devices sector. Europe on the other hand, has no top-10 medical device clusters and therefore appears to have a greater share of medical device innovation taking place outside clusters, as was noted earlier. Similar patent share-cluster share differences between continents do not appear to manifest themselves in the medical life sciences sector. In Europe the opposite pattern is found: Europe has 30% of medical life science clusters and only 25% of patent output, suggesting a proliferation of smaller clusters. These differences in the spatial distribution of clusters point towards different historical development paths of the health technology sub-sectors.

5.3.2 Knowledge Networks

Doubt about the effectiveness of physical proximity, has moved theoretical attention to "relational" proximity. Accordingly, it is assumed that physical proximity only benefits innovation if the local actors see opportunities in collaboration, and that relational proximity can also work over large distances.

In this study knowledge networks are measured through ratios of the number of network links per cluster or inventor. These network links are derived from co-invention or inventor-assignee relationships. Ratios are used because the size of networks is often dependent on the size of the clusters (nodes) and the network itself (Wasserman and Faust 1994). Most knowledge network indicators of the sector appear to be stable, showing similar values for all three periods, although the knowledge networks are growing and clusters are therefore becoming more interconnected. Network reach increased slightly from 32.8 to 35.2 links to other clusters (average). Network density also increased somewhat, from 90.5 to 109.2 inter-cluster links in total per cluster (average). The amount of knowledge inflow and knowledge outflow per inventor has remained mostly constant at 0.54-0.62 to 0.63-0.64 respectively, suggesting that the presence of multinational corporations in clusters has remained stable. Stable agglomeration, cluster spatial distribution, and stable or slow-growing knowledge networks confirm the view that the health technology sector is in a mature development stage (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). No meaningful spatial shifts and no substitution of agglomeration advantages by networks is observed.

There are two notable differences between the co-invention knowledge networks of the sub-sectors (see table C.3, appendix C.2). First, the medical devices sector has a much lower number of co-invention links per inventor (0.35), compared to medical life sciences (0.59). More frequent inter-cluster research collaborations in the medical life sciences fits with the understanding that science-based sectors, because of their more codified knowledge base, have a greater prevalence of long-distance research collaboration (Stankiewicz 2002; Gertler and Levitte 2005). Despite the higher number of co-invention links per inventor in the medical life sciences sector, the network reach and network density of both sub-sectors is similar, in fact the network density of the medical devices sector (124.3 total links per cluster) is higher than that of the medical life sciences sector (101.7 links). A second difference are higher knowledge inflow and outflow from and to multinational corporations headquartered outside the cluster. The medical devices sector has 0.66 inbound and 0.79 outbound links per inventor, higher than the medical life sciences sector with 0.55 inbound and 0.57 outbound links. The higher value for medical devices suggests that multinational corporations' research activity plays a greater role in the medical devices sub-sector when compared to the medical life-sciences sub-sector (Gertler and Levitte 2005). The medical life-sciences sub-sector is well known for its distinct innovation and investment pattern of start-ups, which are later acquired by large multinational pharmaceutical companies (Booth 2016).

Table 5.1: Health technology cluster, agglomeration and knowledge network characteristics 2000-2011.

Indicators	**2000-2003**	**2004-2007**	**2008-2011**
Clusters and Agglomeration			
Total patents	68,303	65,519	72,051
- Patents in North America	37,176 (54%)	34,995 (53%)	38,405 (53%)
- Patents in Europe	16,722 (24%)	14,776 (23%)	16,062 (22%)
- Patents in Asia	12,979 (19%)	14,388 (22%)	16,176 (22%)
- Patents in Rest of World	1,427 (2%)	1,360 (2%)	1,408 (2%)
Total Clusters	215	214	219
- Clusters in North America	129 (60%)	129 (60%)	133 (61%)
- Clusters in Europe	47 (22%)	47 (22%)	47 (21%)
- Clusters in Asia	32 (15%)	32 (15%)	32 (15%)
- Clusters in Rest of World	7 (3%)	6 (3%)	7 (3%)
Clustered patents	32,197 (47%)	28,497 (43%)	30,332 (42%)
Patents per cluster, average	149.8	133.2	138.5
Cluster size Gini coefficient	0.67	0.67	0.67
Corporate patenting share	75.4%	74.9%	73.4%
Knowledge Networks (cluster average)			
Co-invention links per inventor	0.47	0.51	0.51
Network reach (unique links per cluster)	32.8	33.2	35.2
Network density (total links per cluster)	90.5	97.3	109.2
Knowledge inflow (links per inventor)	0.54	0.62	0.59
Knowledge outflow (links per inventor)	0.63	0.64	0.64
Median co-invention distance (km)	48	51	50

5.3.3 Cluster Spatial Distribution

To understand shifts in the spatial distribution of health technology more deeply, the 10 largest clusters (by patents), newly emerged clusters, fastest-growing clusters, and fastest-declining clusters during the 2000-2011 period, are analyzed in this sub-section. Table 5.2 provides an overview of the cities containing the ten largest health technology clusters during three four-year periods, from 2000 to 2011. The cut-off of 10 largest clusters is chosen because for smaller clusters the share of global innovation output already falls to 1% or less. Due to measurement uncertainties associated with using patent data, analysis of clusters with a 1% share or less may be based on data within the margin of error. Clusters are studied over a longer time period to reveal shifts in innovation activity between cities and countries. The analysis focuses on the location of the clusters and on changes in rank position and relative size, which provide a clear indicator of local and global cluster spatial dynamics.

The aggregate health technology sector has a relatively stable top-10, with eight clusters maintaining their position in the top-10 with approximately the same share of global patent output. Among the top-10 clusters, San Francisco is the only cluster experiencing a changing trajectory, moving from from first place, and a 4% share in 2000-2003 to fourth place, and a 2% share in 2008-2011. The ninth or tenth placed cluster varies, with Osaka taking tenth place in 2000-2003, Tel Aviv ninth place in 2004-2007, and Seoul tenth place in 2008-2011. Of the 10 largest clusters, eight are in the United States, up to two are in Japan, and at times one is in Israel (2004-2007), and one is in South Korea (2008-2011). Among the eight American clusters, four are found in a single state, California (San Francisco, Los Angeles, San Diego, and San Jose), which indicates a significant amount of spatial concentration. The relative stability of the cluster ranking reinforces the view that the health technology sector is relatively mature (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). The decline of San Francisco shows that cluster development trajectories can be distinct and in a different direction as compared to other clusters in the same country or state. In the United States, a trend of life sciences research shifting from larger to smaller cities was noted recently (JLL 2012; Giuliano, Kang, and Yuan 2019).

The top-10 health technology clusters are similar to the largest biomedical (medical life sciences) clusters identified by Catini et al. (2015). Catini et al. (2015) use the PubMed database, which contains scientific medical research, and they identify Boston, Tokyo, New York, Washington, Seattle, Los Angeles, and San Francisco, among other cities, as being among the world's largest biomedical clusters. Based on the 10 largest clusters alone, there is no clear evidence of a global shift in innovation activity towards Asia (hypothesis 1, Dicken (2007)). However, a top-10 country ranking (see table C.4, appendix C.2) reveals a consistently rising rank and share of global health technology patents for South Korea, and Taiwan, and consistent declines in global share for Germany, the United Kingdom, Canada, and Sweden.

Table 5.2: Cities with 10 largest health technology clusters 2000-2011 (share of world health technology patents).

Rank	**2000-2003**	**2004-2007**	**2008-2011**
1	San Francisco, US (4%)	Tokyo, JP (4%)	Tokyo, JP (4%)
2	Tokyo, JP (4%)	New York, US (3%)	New York, US (3%)
3	New York, US (3%)	Boston, US (3%)	Boston, US (3%)
4	Boston, US (3%)	San Francisco, US (3%)	San Francisco, US (2%)
5	Los Angeles, US (2%)	Los Angeles, US (3%)	Los Angeles, US (2%)
6	Washington, US (2%)	San Diego, US (2%)	San Diego, US (2%)
7	San Diego, US (2%)	Washington, US (2%)	Washington, US (1%)
8	Seattle, US (1%)	San Jose, US (1%)	San Jose, US (1%)
9	San Jose, US (1%)	Tel Aviv-Yafo, IL (1%)	Seattle, US (1%)
10	Osaka, JP (1%)	Seattle, US (1%)	Seoul, KR (1%)

As noted earlier, aggregate health technology clusters are a combination of their sub-sectors (see table C.5, appendix C.2). Six of the cities host both top-10 medical device and top-10 medical life sciences clusters: Boston, Los Angeles, New York, San Diego, Seoul, and Tokyo, which are all large "global" cities (Taylor 2004; Ichikawa, Yamato, and Dustan 2017). The high frequency with which cities host top-10 clusters of both sub-sectors (60%) supports the decision to combine medical device and medical life science clusters in the analysis.

Newly emerged aggregate health technology clusters are those that did not meet the minimum cluster threshold during the 2000-2003 period but are identified during the 2008-2011 period.

The new clusters are Aarhus (Denmark), Bern (Switzerland), Springfield (United States), and Tsu (Japan). Aarhus and Bern are both small European cities (population below 300,000) and are home to relatively large research universities carrying the names of both cities (student populations of 18,000-38,000). Springfield refers to the Springfield-Hartford corridor in Massachusetts and Connecticut, which is home to a number of universities, including the University of Connecticut and the University of Massachusetts at Amherst. Tsu is a small Japanese city (population 280,000) and is the capital of Mie prefecture. Tsu is located roughly half-way between Osaka and Nagoya. Mie University is its most prominent institution of higher learning in the city (7,500 students).

A common feature of all new clusters is the presence of a local university. In the case of Bern, the seeds for a life sciences cluster were planted here around 1949 with the foundation of Central Laboratory Blood Donation Service in Bern, under the umbrella of the Swiss Red Cross. In 1951, the laboratory was empowered by the government to manufacture products from donated blood plasma. In the years that followed, the organization transformed itself into a highly innovative and globally active R&D firm, now named CLS Behring, with a focus on blood-related drugs, including the use of monoclonal-antibody technology. Local and regional research collaboration was undertaken both with the University of Bern and ETH Zurich, and later on worldwide through subsidiaries located abroad.

The aggregate growth of clusters is calculated by comparing the 2000-2003 and 2008-2011 periods. The 10 fastest-growing clusters (by patents) and the 10 fastest-shrinking clusters (by patents) are shown in table 5.3 and 5.4. Among the fastest-growing clusters, six are located in Asia (Israel included), with Seoul and Tokyo growing by more than 400 patents. Among these clusters Beijing has the highest growth rate (+224%), followed by Seoul (+193%) and Daejeon (+166%). Four clusters from the United States are also included, of which the fastest-growing is Denver. The presence of large and fast-growing health technology clusters in Asia supports the view that a global shift of healthcare innovation activity towards Asia is taking place (hypothesis 1, Dicken (2007)), although it appears to be concentrated in specific clusters and countries.

Table 5.3: Cities with the fastest-growing health technology clusters 2000-2011 (absolute growth and growth rate).

Rank	**City**	**Δ Patents**	**Rate**
1	Seoul, KR	451	193%
2	Tokyo, JP	407	26%
3	Tel Aviv-Yafo, IL	196	43%
4	Taipei, TW	151	71%
5	Daejeon, KR	133	166%
6	Denver, US	123	42%
7	San Jose, US	97	12%
8	Beijing, CN	68	224%
9	Boston, US	59	3%
10	Seattle, US	59	7%

The top-10 *shrinking* clusters (see table 5.4) are all found in North America and include both major cities like Montreal, New York, Washington, and San Francisco, as well as smaller cities, many of which appear to be university towns. These include: Indio (University of California at Riverside), Birmingham (University of Alabama at Birmingham), New Haven (Yale University), and Pasadena (California Institute of Technology). The clusters experiencing the greatest relative decline are New London, which is about 75 km from New Haven, and Boise, Idaho (both -77% growth). The clusters experiencing the largest absolute decline are Washington DC (-496) and San Francisco (-777).

The presence of clusters in the United States among both the top-10 growing and top-10 declining clusters suggest considerable spatial dynamics within the country, with some clusters shrinking and others growing during the same time period. This reflects changes in the health technology sector that go beyond the broader trends described earlier, such as a shift of innovation activity from one country to another. As noted earlier, within the United States there is a trend of healthcare innovation activity shifting from large to smaller cities (JLL 2012). However, the scale of the decline of United States clusters appears to be greater than the amount of patent growth: the four fastest-shrinking clusters “lose” 1,549 patents (Boise, New York, Washington, and San Francisco) whereas the four fastest-growing clusters in the United States “gain” just 338 patents (Denver, San Jose, Boston, and Seattle). Large gains instead occur in clusters in South Korea, Japan, Israel, and Taiwan, thus providing support for hypothesis 1, which proposes a global shift towards Asia.

Table 5.4: Cities with the slowest-growing (fastest-shrinking) health technology clusters 2000-2011 (absolute growth).

Rank	City	Δ Patents	Rate
138	Birmingham, US	-45	-65%
139	Indio, US	-49	-46%
140	New London, US	-52	-77%
141	New Haven, US	-54	-36%
142	Montreal, CA	-55	-37%
143	Pasadena, US	-70	-36%
144	Boise, US	-107	-77%
145	New York, US	-169	-7%
146	Washington, US	-496	-33%
147	San Francisco, US	-777	-30%

5.4 Cluster Innovation Performance

The cluster innovation performance model is intended to provide insight into the factors that influence, or are associated with, cluster innovation performance in the health technology sector. The model is relatively simple by only assuming direct relations (see figure 3.1, chapter 3). A brief discussion of the model factors (indicators) is followed by an analysis of the model estimation results. The model contains two different kinds of factors: factors related to the national innovation system and path dependence are seen as “influences” (causality is one-way, towards innovation performance). Factors related to agglomeration and networks are viewed as “associated” with innovation performance, because reverse causalities likely exist (see chapter 3 for a discussion of the research model). An overview of the factors and their indicator values is presented in table 5.5.

Aside from the logarithmic transformation of all model indicators, the cluster size, and adjacency indicators have also undergone a 10^{-5} transformation to ensure that their estimated model coefficients are in a similar range of the other indicators. For this reason the indicator range for cluster size and adjacency appear to be relatively small. The national innovation system indicator tends towards higher values because a large number of clusters is located in high-quality innovation systems such as the United States, Switzerland, and Japan, and only a small number of clusters is found in lower-quality innovation systems such as Italy, Spain, and China (Schwab and Sala-i-Martin 2015). The national innovation system indicator is a composite indicator based on research investment, the quality of the higher education system, university-industry collaborations and protection of intellectual property.

The knowledge base of the two sub-sectors is accounted for in the model using a dummy variable, which indicates whether a cluster has an engineering and design knowledge base (medical device clusters). The implementation and testing of the model is described in detail in section 3.6.2 and 3.6.3 (chapter 3). The model estimation results are within the accepted boundaries for multicollinearity (Variance Inflation Factor < 2) and normally distributed residuals (Shapiro-Wilk test $p < 0.10$). Heteroscedasticity is within the accepted boundaries (Breusch-Pagan $p < 0.10$). Therefore, the basic assumptions of Ordinary Least Squares (OLS) regression are being met and the correlations in the model results are robust. An OLS regression is used for an initial exploration of the correlation and associations between various indicators.

Table 5.5: Statistical summary of health technology model indicators (log-transformed, $n = 219$).

Indicator	**Measurement**	**Minimum**	**Mean**	**Maximum**
Innovation performance, IVP	Patent citations	-2.30	-0.0632	3.25
Cluster size, PAT	Patent count	-2.30	-2.29	-2.14
Adjacency, ADJ	Patent count	-2.30	-2.19	-0.334
Regional specialization, SPE	Patent count	-2.25	-1.80	0.0218
Corporate research, CRP	Patent assignees	-2.30	-0.289	0.0953
National innovation system, NSQ	Composite indicator*	1.18	1.66	1.73
Knowledge inflow, MNC	Patent inventor-assignee network	-2.30	-0.617	1.41
Knowledge outflow, LAB	Patent inventor-assignee network	-1.40	-0.395	0.879
Network reach, NET_S	Patent co-invention network	-1.20	1.03	2.86
Network density, NET_W	Patent co-invention network	-2.11	-0.615	0.663
Past innovation performance, IVP_P	Patent citations (previous period)	-2.30	0.756	3.55

* Composite indicator of national private and public sector research investment, quality of higher education system, university-industry collaborations and protection of intellectual property.

The health technology model estimation results in table 5.6 are now discussed. Results are both given for partial models and their set of individual indicators. For each partial model, adjusted ΔR^2 is provided to assess the improvement of the outcomes compared to the control model.

The **agglomeration model** consists of two scale-based agglomeration indicators (cluster size PAT and adjacency ADJ), a specialization-based agglomeration indicator (regional specialization SPE), and a qualitative indicator which describes the presence of corporate research (CRP). The results in table 5.6 show that the partial models' predictive power (adjusted ΔR^2) is 0.087. The scale-based indicators measure the number of sub-sector patents produced inside the cluster, and the number of patents produced in other clusters of the same sub-sector located within 200 km of the cluster (adjacency).[2] Cluster size has a positive and statistically significant association with the dependent variable, suggesting that positive scale effects exist in health technology clusters: spatial proximity facilitates transactions and collaboration between actors, raising productivity, and provides an environment with shared values, beliefs, and trust (Morgan 2004; Capello 2009; Leamer and Storper 2014). The negative association with adjacency suggests that at distances of ~200 km spatial proximity increases competition for resources and talent, and causes other negative scale effects (Martin and Sunley 2003), a somewhat unexpected outcome given the generally positive view of the neighborhood effect (Ó hUallacháin and Leslie 2007; Charlot, Crescenzi, and Musolesi 2014).

Regional specialization is a measure of sectoral cluster patenting relative to patenting from *all* other sectors taking place within the cluster's geographic boundaries. This indicator is statistically significant and positively associated with cluster innovation performance. The benefits of specialization in a cluster can be attributed to a better match with specific needs for high-quality labor, services, and specialized learning (Giuliano, Kang, and Yuan 2019). Further, corporate research measures the share of cluster patents owned by private sector corporations. This indicator also has a positive and statistically significant association with the dependent variable. This suggests that a cluster's local *corporate* strategy and absorptive capacity enhance innovation performance more than *public* strategy and absorptive capacity at local university (Fu 2008; Qiu, Liu, and Gao 2017). To summarize, the agglomeration model estimation results provide partial support for hypothesis 3 (economies of scale), and support for hypothesis 4 (regional specialization) and hypothesis 5 (corporate share).

The **national innovation system model** is estimated using one indicator: national innovation system quality (NSQ). National innovation system quality is a composite measure that incorporates private and public sector research investment, quality of higher education system, university-industry collaborations and protection of intellectual property at the national level. The indicator is not statistically significant and the partial model's explanatory power is zero, or to be precise: adjusted ΔR^2 is -0.005. The quality of the national innovation system therefore does not appear to influence cluster innovation performance in any way, and as a result hypothesis 6 (national innovation system) is rejected. The lack of significance may be due to the lack of diversity among national innovation systems, as indicated above: mainly highly developed national innovation systems are engaged in the sector.

The **knowledge network model** encompasses two indicators related to knowledge inflow (MNC) and knowledge outflow (LAB), and two indicators related to the cluster's position (degree cen-

[2] For illustration purposes, 200 km is equivalent to approximately 2 hours of non-stop highway driving. It is approximately equal to the distance from Amsterdam to Brussels, Shanghai to Huangzhou, or Los Angeles to San Diego. Approximately 80% of clusters are located within 200 km of another health technology cluster.

trality) in the inter-cluster knowledge co-invention network (NET_S and NET_W). The knowledge flow indicators are derived from the inter-cluster inventor-assignee network, with an outbound inventor-assignee link indicating knowledge outflow and an inbound link indicating inflow. Both knowledge flow indicators and the weighted degree centrality indicator are divided by the number of inventors. The partial models' predictive power is an adjusted ΔR^2 of 0.139, which is larger than the predictive power of the agglomeration model described before. The relatively high explanatory power of the agglomeration and knowledge network models can be interpreted as an indicator that both agglomeration and knowledge networks play an important role in health technology clusters.

Two indicators, knowledge outflow and co-invention network reach, are statistically significant and positively associated with cluster innovation performance. These results suggest that network connectedness, including through the presence of multinational corporations' remote labs within a cluster, contributes positively to a cluster's innovation performance. This result aligns well with the observed higher frequency of long-distance research collaborations in healthcare related sectors, such as pharmaceuticals (Alkemade et al. 2015). The knowledge network model estimation results provide support for hypothesis 8a (outbound knowledge flow) and hypothesis 9 (network reach).

Next, the **path dependence model** is estimated using only one indicator: past innovation performance (IVP_P). Past innovation performance is calculated from patent data of the preceding 2004-2007 period. It appears that past innovation performance has a high correlation with the dependent variable ($R^2 = 0.87$, see the correlation matrix table B.8, appendix B.2). Therefore, it is not surprising that past innovation performance has a positive and statistically significant association with cluster innovation performance during the more recent period. The model's predictive power is indicated by an adjusted ΔR^2 of 0.486, which is the highest increase in explanatory power of all partial models compared to the control model.

It is also notable that the knowledge base dummy variable is statistically significant in the path dependence model estimation, suggesting that there may be some differences in path dependence between the medical life sciences, and medical devices sub-sectors. The path dependence model result provides clear support for hypothesis 11. Hypothesis 11 suggests a positive influence of past innovation performance on current innovation performance as path dependence is seen as accumulating over time. During a stable and mature development phase, clusters (and organizations) that have performed well in the past tend to continue to do well due to the accumulation of knowledge, experience, skills, trust, reputation, etc. (Boschma and Frenken 2006; Crescenzi and Rodríguez-Pose 2011; Vergne and Durand 2011; Trippl et al. 2015; Crescenzi and Jaax 2017). The relatively strong influence of path dependence supports the view that the health technology sector is relatively mature (Martin and Simmie 2008; Ter Wal and Boschma 2011).

The final partial model, the combined **agglomeration and network** model includes indicators which were included in the partial agglomeration, national innovation system, and knowledge network models described earlier. To avoid issues of multicollinearity the network reach indicator is excluded from the model estimations (see also table B.8, appendix B.2). The model estimation results of the agglomeration and knowledge network model are similar to those of the earlier partial models, except that regional specialization falls just below the 90% statistical significance threshold. The model's predictive power (adjusted ΔR^2 of 0.117) is higher than that of the agglomeration model, a fact that can be explained by the addition of some relevant knowledge network variables. However, the combined model's predictive power is lower than that of the knowledge network model. This is likely because one knowledge network factor was excluded from the combined model estimation.

Table 5.6: Health technology cluster innovation performance model estimation results 2008-2011.

Indicators	**Control**	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration and Network**
Cluster size		5.2 (1.3)***				6.1 (1.5)***
Adjacency		-0.25 (0.13)*				-0.28 (0.15)*
Regional specialization		0.31 (0.15)**				0.24 (0.16)
Corporate research		0.29 (0.079)***				0.23 (0.084)***
National innovation system			-0.48 (0.47)			-0.40 (0.51)
Knowledge inflow				0.059 (0.093)		0.15 (0.093)
Knowledge outflow				0.43 (0.14)***		0.39 (0.14)***
Network reach				0.36 (0.067)***		
Network density				-0.17 (0.13)		-0.065 (0.14)
Past innovation performance					0.69 (0.073)***	
Knowledge base (dummy)	-0.39 (0.38)	-0.053 (0.11)	-0.12 (0.11)	0.083 (0.13)	0.20 (0.066)***	0.037 (0.15)
Constant	1.5 (0.37)***	12. (3.0)***	0.81 (0.80)	-0.38 (0.16)**	-0.71 (0.077)***	15. (3.7)***
Adjusted R^2	0.004	0.089	-0.001	0.143	0.490	0.120
Adjusted ΔR^2		0.085	-0.005	0.139	0.486	0.116
Clusters (n)	219	219	219	219	219	219

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Agglomeration and knowledge networks develop and accumulate over time, and therefore they can also be seen as part of a cluster's path dependence. As a rough estimate of their impact, the predictive power of the agglomeration and knowledge network models can be compared to that of the path dependence model. In the health technology sector the knowledge network and agglomeration factors together appear to account for approximately 47%[3] of the predictive power of the path dependence model. Other factors such as knowledge, skills, reputation, experience, and specialized resources that were acquired or accumulated over time (Simmie and Strambach 2006; Martin and Simmie 2008) likely account for the remainder of the path dependence correlation.

When comparing the aggregate health technology model results discussed above to those of the medical life sciences and medical devices sub-sectors, there are some small but interesting differences (see appendix C.2). Compared to the aggregate health technology sector, agglomeration factors, and path dependence appear stronger in the medical devices sector. The predictive power of the medical devices agglomeration model (adjusted R^2 of 0.250) is greater than that of the medical devices knowledge networks model (adjusted R^2 of 0.142), whereas the opposite is true in the health technology model that includes both sub-sectors. The stronger agglomeration factor in the medical devices sector can be viewed from the perspective of its engineering and design knowledge base. In sectors with an engineering and design knowledge base the importance of tacit knowledge and inter-personal interaction is typically emphasized, and therefore these sectors should benefit more from agglomeration which enables frequent personal interactions (Asheim and Coenen 2005; Carlsson 2013). The predictive power of the medical devices path dependence model is also relatively high (adjusted R^2 of 0.773, see appendix C.2) when compared to the aggregate health technology model (adjusted R^2 of 0.490). The greater path dependence of medical device clusters can be connected to the sub-sector's stable growth trajectory as compared to the medical life sciences sector (see figure 5.1). The medical life sciences sector is known to undergo boom-and-bust cycles, whereby there are periods of very high private investment, followed by periods of low private investment, which make its innovation output more volatile (Booth 2016).

5.5 Discussion

This section provides an analysis of the results presented in this chapter. The section begins with an evaluation of the relevant hypotheses and is followed by a further discussion of some additional observations. A total of 10 hypotheses are evaluated (see table 5.7), with a mix of not rejected, rejected, and partially rejected evaluation outcomes.

Hypothesis 1 addresses the spatial distribution of medical health technology clusters and posits that new and fast-growing clusters are mainly located in Asia. This outcome is partially rejected by the analysis: while only a few new clusters are created during the study period and they are located not just in Asia (1 new cluster) but also in Europe (2 new clusters) and North America (1 new cluster), the fastest-growing clusters are located predominantly in Asia (see section 5.3). The lack of new cluster-formation in Asia could be due to the relatively mature development phase of the health technology sector, which is also confirmed by the stability of the sector's knowledge network structure (Ter Wal and Boschma 2011). The mature development phase could make it more difficult for new clusters (e.g. from Asia) to enter and grow because the accumulated

[3]calculated by adding the adjusted ΔR^2 values of the agglomeration and knowledge network models and dividing by the path dependence model.

knowledge and skills of incumbents acts as a barrier (Lee and Lim 2001). Evidence for a high level of knowledge and skills accumulation is supported by the strong influence of path dependence on cluster innovation performance (see section 5.4).

Agglomeration is addressed by way of hypotheses 3-5. Hypothesis 3 covers scale-based agglomeration and it receives partial support: cluster size is positively associated with cluster innovation performance, but adjacency has a negative association, suggesting positive agglomeration at a smaller spatial scale and negative agglomeration effects at a larger spatial scale. This outcome can be understood when considering the advantages and disadvantages of agglomeration. At a smaller spatial scale the advantages of spatial proximity, such as increased opportunities for collaboration and knowledge spillovers (Morgan 2004; Capello 2009), appear to outweigh the disadvantages of increased competition for resources, congestion, higher cost, and a lower quality of life often found in major urban areas (Richardson 1989; Zheng 2001; Martin and Sunley 2003). Clusters with a large adjacency value are found near other clusters, which are usually located within large urban corridors or conurbations (for illustration, see figure A.1, chapter 4). In this sense there is a limit to agglomeration economies when sectoral clusters are located within very large urban corridors.

Hypothesis 4 posits that regional specialization has a positive effect and the results support this view. High regional specialization in the health technology sector implies that other sectors within the same region are smaller. Therefore, the benefits of lower congestion, competition for resources, and costs likely out-weigh the potential benefits if inter-sectoral collaborations and knowledge spillovers, which might be found in larger regions (Jacobs 1969; Camagni and Capello 2002; Capello 2009). This effect is most clearly visible in the medical devices sector (see table B.10, appendix C.2).

Hypothesis 5 posits a positive relationship between corporate research activity and cluster innovation performance: this relationship is confirmed. Hypothesis 6 which suggests that the national innovation system has a strong influence on cluster innovation performance is rejected by the empirical results. It appears that national institutions and policies do not influence healthcare cluster innovation performance in a significant way (Strange 1996; Binz and Truffer 2017). Hypotheses 7-10 are about knowledge networks. Hypotheses 7 and 8 cover knowledge inflow and outflow. Hypothesis 8, which claims a positive association of knowledge outflow with cluster innovation performance, is not rejected. This result fits with the view that multinational corporations, which are seen as the main facilitators of inter-cluster knowledge flows, tend to re-enforce already thriving clusters (De Propris and Driffield 2005; Liu and Buck 2007; Østergaard and Park 2015).

Hypothesis 9 and 10 address the knowledge network structure and the empirical results show a positive relationship between network reach and cluster agglomeration (hypothesis 9). The association between network density and cluster innovation performance is rejected (hypothesis 10). The knowledge network hypotheses suggest that "conventional wisdom" with regards to knowledge networks seems to apply to the health technology sector. This is to say that negative or reverse knowledge flows (Frost and Zhou 2005; Ambos, Ambos, and Schlegelmilch 2006) are not observed from the empirical results. Hypothesis 11 proposes that path dependence positively influences cluster innovation performance, and this view is not rejected by the empirical results. Path-dependence appears especially strong in the medical devices sector (see table B.10, appendix C.2).

Table 5.7: Evaluation of hypotheses for the health technology sector.

Hypotheses	**Evaluation**
Hypothesis 1: New and fast-growing sustainability technology clusters are more frequently located in Asia.	Partially Rejected
Hypothesis 3: Agglomeration has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 4: Regional specialization has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 5: Corporate research activity has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 6: The quality of the national innovation system has a positive influence on cluster innovation performance.	Rejected
Hypothesis 7: Knowledge inflow has a positive association with cluster innovation performance.	Rejected
Hypothesis 8: Knowledge outflow has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 9: The reach of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 10: The density of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Rejected
Hypothesis 11: Past cluster innovation performance has a positive influence on current cluster innovation performance.	Not Rejected

In addition to discussing the results based on the hypotheses, some further observations should be made related to the healthcare sector's development stage, the global spatial distribution of health technology clusters, the role of multinational corporations and differences between the medical devices and medical life sciences sub-sectors. The characterization of the health technology sector as being in a mature development phase is supported by the empirical results, as the spatial distribution and knowledge networks of the clusters appears to be mostly stable during the study period (table 5.1 and 5.2). However, the results also show some important dynamic patterns. First is the decline and subsequent recovery of medical life sciences patent output (figure 5.1). Second is the rapid growth of (+166 to +224%) of certain clusters in Asia, including Seoul, Daejeon, and Beijing. At the same time some large clusters in the United States are declining, including Washington and San Francisco (-33 and -30%, see table 5.3 and 5.4). These observations provide a nuanced perspective on a sector that has reached a mature development phase but is also involved in certain socio-technological transformations (Ohta 2019).

Also noteworthy is the large role of knowledge outflow, which can be facilitated by the remote labs of multinational corporations. The frequency at which a patent invented in a cluster is owned by an entity from outside the cluster (knowledge outflow) is more than three times larger than the number of co-invention links per inventor (0.64 compared to 0.18, see table 5.1), confirming the perspective that multinational corporations create important global knowledge "pipelines" between technology clusters (Bathelt, Malmberg, and Maskell 2004; Morrison, Rabellotti, and Zirulia 2013). In addition to this the knowledge outflow indicator is also positively associated with cluster innovation performance (hypothesis 8a). Finally the medical devices sub-sectors shows an important deviation from the medical life sciences sector in terms of its spatial pattern: just 24% of medical device patents are found in clusters, as compared to 72% for the medical life sciences. This is a notable difference because it could be interpreted as medical device clusters holding limited agglomeration advantages, which might reduce clustering. It could also be interpreted as clusters not being the main source of growth for the medical devices sector, with new innovations taking place more frequently outside clusters (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015).

5.6 Conclusion

This chapter has provided an overview of the spatial distribution, knowledge networks, and the characteristics associated with cluster innovation performance in the health technology sector. Overall the sector follows a relatively stable development trajectory, with no or limited changes in patent output, clusters, and cluster characteristics. The analysis does reveal a notable knowledge gap, concerning the spatial concentration of the medical devices sub-sector. The sub-sector has a very low clustering rate compared to medical life sciences, which appears to be due to its specific evolutionary growth path, at least with regards to Europe (Klein, Banga, and Martelli 2015). The observation raises questions about the relevance of clusters in the medical devices sub-sector, as only 24% of its patents are produced in clusters. The observation also creates some ambiguity with regard to the view that the medical devices sector has an engineering and design knowledge base, whose innovation process involves frequent inter-personal interactions, which are presumably facilitated by agglomeration in clusters (Stankiewicz 2002; Asheim and Coenen 2005).

Another notable result is evidence of a “global shift” of health technology innovation activity towards Asia. The growth of some large Asian clusters and the decline of some large North American clusters fits within a broader narrative of “global shifts” towards Asia (Dicken 2007; Malecki 2014). Yet the situation of individual clusters seems more nuanced, as some North American clusters, such as Denver, are also among the world’s fastest-growing, which is presumably due to internal shifts taking place in the United States, of healthcare innovation moving from large to smaller cities (JLL 2012; Giuliano, Kang, and Yuan 2019). Also notable is the lack of statistically significant results for the national innovation system, knowledge inflow, and network density, with regards to cluster innovation performance. The concentration of health technology clusters in countries with advanced national innovation systems may explain the factor’s lack of statistical significance. In a similar way knowledge inflow and network density may be important, but not serve as distinguishing factors in explaining innovation performance, possibly due to the fact that the sector has a relatively stable and mature knowledge network.

In the next chapter (chapter 6) a similar analytical framework is applied to the sustainable energy technology sector. The results of this chapter and the next chapter are compared in detail and benchmarked against reference high technology sectors in chapter 7.

Chapter 6

Sustainable Energy Technology Clusters

6.1 Introduction

The sustainable energy technology sector is defined based on seven technological sub-sectors: biofuels, electric vehicles, electricity storage, fuel cells, hydrogen technology, photovoltaics, and wind turbines, which play an important role in addressing the global challenge of climate change and the development of zero or low carbon emitting energy technologies (European Commission 2013, 2019; Intergovernmental Panel on Climate Change 2015, 2018; United Nations 2015). This chapter provides a descriptive analysis of the spatial distribution, agglomeration, and knowledge networks of sustainable energy technology clusters, and an explanatory analysis of their innovation performance.

The chapter begins with a profile of the sustainable energy technology sector and its sub-sectors (section 6.2), which includes a description of the sector's growth trajectory, knowledge base, innovation actors, and technological and market trends. There is considerable heterogeneity across the seven sustainable energy technology sub-sector, which is addressed in the following way: in the first instance the sustainable energy technology sector is treated as a single sector, because the research focus is on socio-technological transformations. Heterogeneity among the sub-sectors is addressed in the second instance, whenever there are clear divergences from the average. Section 6.3 provides a description of the spatial distribution of patents, and of agglomeration and knowledge network characteristics. The observations made over a 12-year period from 2000 to 2011 allow changes in patenting locations and patterns to be observed within the context of "global shifts" (Dicken 2007) and the sector's development trajectory (Ter Wal and Boschma 2011). The association between sustainable energy technology cluster characteristics and innovation performance is analyzed using a regression model in section 6.4. Section 6.5 covers the evaluation of the hypotheses and a discussion of the empirical results. The chapter concludes with an overview of the main research findings and their implications (section 6.6).

6.2 Sector Profile

The sector profile provides an overview of the sustainable energy technology sub-sectors: biofuels, electric vehicles, electricity storage, fuel cells, hydrogen technology, photovoltaics, and wind turbines. The sector profile includes the growth trajectories of the sub-sectors during the 2000-2011 period (subsection 6.2.1), an overview of the sub-sectors' knowledge base and recent technological trends (subsection 6.2.2), and a discussion of the main innovation actors and the size of the sub-sectors (subsection 6.2.3). The knowledge base and the institutional landscape are seen as important factors that influence cluster innovation performance (Breschi and Malerba 1997; Iammarino and McCann 2006).

6.2.1 Sector Growth

The sustainable energy technology sector is being driven by a growing demand for low-carbon technologies. R&D is focused on further improving technological features so that zero-carbon technologies can become competitive with existing carbon-based energy and transportation alternatives. As part of a broad policy to address the issue of climate change, sustainable energy is expected to play an important role in reducing the consumption of conventional carbon-based fuels, thus reducing the emission of greenhouse gases and other air pollutants (Algieri, Aquino, and Succurro 2011; REN21 2017). Sustainable energy technologies play a key role in achieving the goals of the Kyoto Agreement and Protocol, the last entering in force in 2005, and the Paris Agreement, which was signed by 197 countries and entered into force on November 4, 2016. As described in the United Nations Framework Convention on Climate Change: "The Paris Agreement's central aim is to strengthen the global response to the threat of climate change by keeping a global temperature rise this century well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius" (Fan 2019b), a goal whose achievement requires a very rapid and global transition towards sustainable energy use (Schleussner et al. 2016).

In addition to climate change goals, a move away from coal and other polluting energy sources also benefits air quality, an issue that has gained considerable political concern in densely populated parts of Mainland China, Hong Kong, and South Korea (Kostka and Zhang 2018; Shapiro 2018; Gross, Buchanan, and Sané 2019), among other places. Another politically salient benefit of renewable energy is their potential for reducing dependence on energy imports, in cases where domestically generated renewable energy can replace imported fossil fuels. This gives sustainable energy technology a security-strategic role in large energy-importing countries such as South Korea, China, Thailand, and Japan (Algieri, Aquino, and Succurro 2011; Vasseur, Kamp, and Negro 2013; Kim 2016; International Energy Agency (IEA) 2019d). Renewable energy technologies and industries can also raise economic growth and international competitiveness and can offer new economic and employment opportunities (Algieri, Aquino, and Succurro 2011), an idea explicitly formulated in South Korea during the Lee Myung Bak administration as its "Green Growth" policy (Kim 2016).

The increased demand for sustainable energy is reflected in rising patent output of the various sustainable energy technology sub-sectors (see figure 6.1). The fastest-growing sectors from 2000-2011 in relative terms are Biofuels (+1,408%), Wind Turbines (+1,361%), and Fuel Cells (+850%). In absolute terms Photovoltaics (+4,763), Electric Vehicles (+4,266), and Electricity Storage (+3,287) are the fastest-growing sub-sectors. The slowest-growing sustainable energy technology sub-sector is Hydrogen Technology (+394 patents, +123%), which is still has double the growth rate of the medical devices (+49%) and medical life sciences sub-sectors (+6.7%) over 12 years. Therefore, especially when compared to the health technology sector, the sustainable energy technology sector in 2000-2011 should be seen as an emerging sector that is likely path creating, due to its high growth rates (Martin and Simmie 2008).

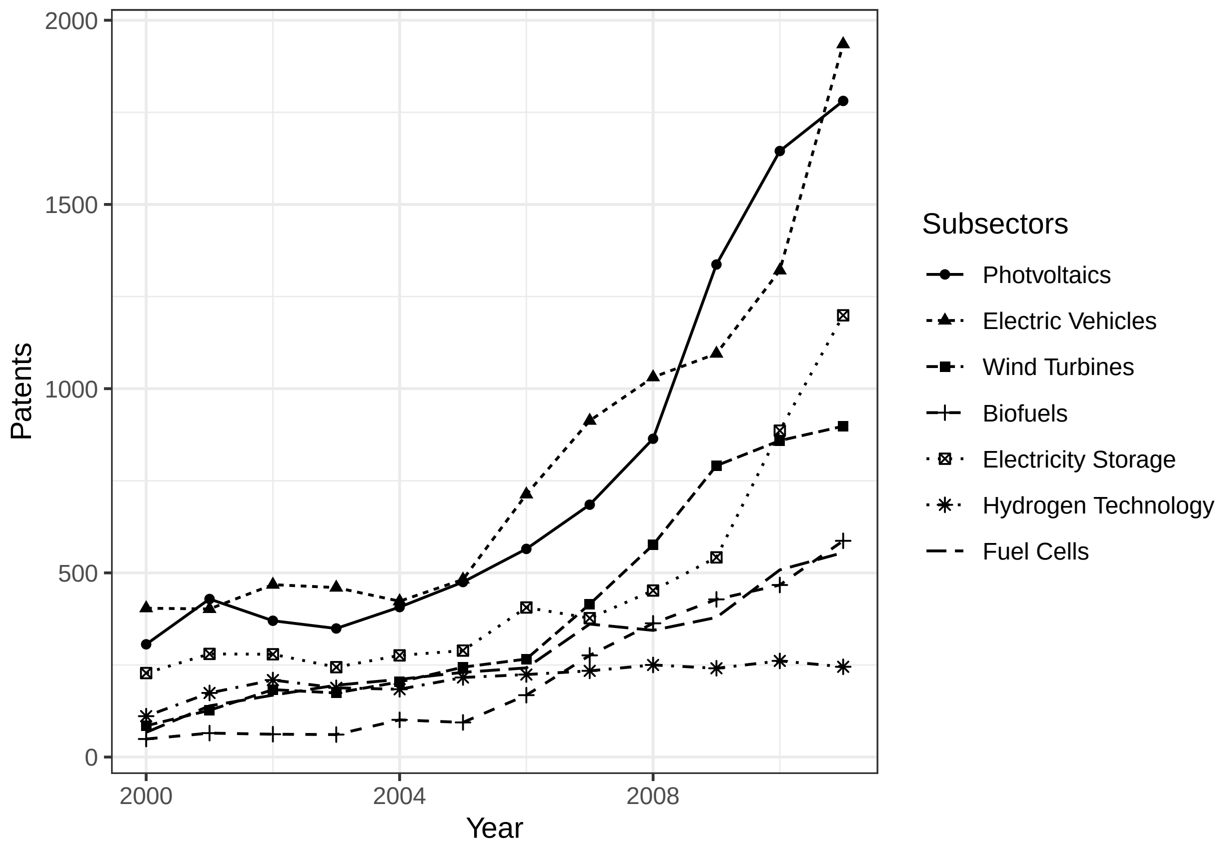

Figure 6.1: Annual sustainable energy technology patent grants by sub-sectors based on application year (source: USPTO).

6.2.2 Sectoral Knowledge Base and Technological Trends

The knowledge base and technological trends are important influences in the innovation process of every sector and they are therefore important background conditions for a sectoral analysis. The knowledge base influences how R&D innovation takes place: the institutions involved, patenting propensity, and the extent to which collaboration between firms, universities, and public research institutions is likely to be established and maintained (Asheim and Coenen 2005; Tidd, Bessant, and Pavitt 2005; Carlsson 2013). A distinction is often made between science- and engineering and design-based sectors. In sectors with a scientific knowledge base, basic (fundamental) research is an important source of innovation and therefore collaboration by industry with universities and public research institutions tends to occur more frequently. Knowledge also tends to be more codified, facilitating collaboration over long distances (Asheim and Coenen 2005; Carlsson 2013). A sector with an engineering and design knowledge base innovate based on close interactions with customers and suppliers, and through "learning by doing" enabling the accumulation of experience and specialized skills (Jeannerat and Kebir 2016).

Most of the sustainable energy technology sub-sectors can be considered as having a scientific knowledge base due to their focus on the development of new materials, which is closely connected to advances in fundamental research (Tidd 2001; International Energy Agency 2016; Binz and Truffer 2017; International Energy Agency (IEA) 2019d). Especially research in electricity storage (rechargeable batteries), fuel cells, and hydrogen technology is focused on the identification and production of novel materials with improved properties, as well as methods for up-scaling the production and extending the life-cycle of these materials and related devices for the conversion and storage of sustainable energy (REN21 2017; International Energy Agency (IEA) 2019d). A significant part of photovoltaics research also involves investigating new materials for the conversion of solar radiation into electricity, with research addressing the challenges of raising the conversion efficiency, and scaling up production (Masson 2017). Biofuels research is closely related to advances in bio and bioprocessing technology, which is also considered a science-based sector (Binz and Truffer 2017).

Two of the sectors can be considered as engineering-based sectors: electric vehicles and wind turbines (Binz and Truffer 2017). Electric vehicle technology is closely related to the automotive industry, and involves technology related to electric motors and related parts (Li et al. 2016). Wind turbine research is primarily focused on optimizing windmill and turbine designs for maximum energy conversion efficiency, as well as efforts to lower installation and maintenance costs (International Energy Agency 2016).

Despite some similarities between sub-sectors in terms of their knowledge base, all sub-sectors cover distinct technologies. Biofuels are fuels derived from biomass, and are primarily used in transportation, and they are produced from wood and various agricultural commodities such as corn, sugar cane, palm oil, etc. Their adoption is partly policy-driven, with countries mandating a certain percentage of fuel to come from biological sources (International Energy Agency (IEA) 2019d). Therefore, innovation in biofuels is primarily directed at developing technologies for the more efficient large-scale production of biofuels, but also towards creating more high-value (co)-products such as aviation fuels, fuels with greater similarity to conventional diesel and petrol (allowing higher blend ratios and use in older unmodified engines), and fuels that have lower aromatic content, which lowers air pollution in terms of toxic hydrocarbons, nitrous oxides, and fine particulate matter (International Energy Agency (IEA) 2019d).

With reference to sustainable transportation, electric vehicles, and electricity storage are closely related from a system perspective. Electricity storage technology (batteries) forms the main technological challenge for making electric vehicles competitive with fossil fuel vehicles in terms of cost and performance, including maximum driving range, and battery charging time (International Energy Agency (IEA) 2019a). Electricity storage innovation is primarily focused on reducing the size, weight, and cost of batteries, relative to their capacity to store energy and to use more environmental-friendly battery materials. This is achieved by the use of new materials and the scaling up of battery manufacturing capacity (International Energy Agency (IEA) 2019a). The large scale production and lower cost of batteries also has the potential to reduce the cost of storing grid and off-grid electricity (i.e. not for transmission), and this can help to address the variability in the production of sustainable energy from sources such as photovoltaics and wind turbines, which depend on the weather and time of day.

An additional energy source for transportation are fuel cells, of which hydrogen fuel cells are the most important sub-group. Fuel cell innovation takes place on a number of different fronts. With respect to the fuel cells themselves, R&D is focused on reducing the cost while increasing the performance and durability of the cells (International Energy Agency (IEA) 2019b). Regarding the production of the energy carrier hydrogen, the majority of hydrogen is currently produced using fossil fuels (also leading to large amount of carbon dioxide emissions) and applied in the chemical and steel industries. However, electrolysis - the process of producing hydrogen from solar/wind electricity and water - is a process that enables hydrogen production with zero carbon emissions. This offers solutions for climate-friendly energy storage, fueling vehicles, decentralized heating (eventually using existing natural gas grids), making synthetic fuels, and using cleaner hydrogen inputs in industrial processes (International Energy Agency (IEA) 2019b). Research on these applications took place during the 2001-2011 study period of this analysis.

The most widely adopted sustainable electricity generation technologies are photovoltaics and wind turbines. Innovation in photovoltaics is primarily focused on the development of new photovoltaic materials and the scaling up of their production. Innovations in solar cell and module production are less rapid (De La Tour, Glachant, and Ménière 2011). There are also innovations of a more practical nature, including for example: solar cells shaped like roof-tiles, facades of buildings, and lamp-post covering. Governments are a dominant actor in terms of stimulating demand for photovoltaic cells through feed-in tariffs, the imposition of solar energy quotas or targets, tax breaks, and other subsidies (De La Tour, Glachant, and Ménière 2011; Grau, Huo, and Neuhoff 2012; Vasseur, Kamp, and Negro 2013). Governments are also stimulating R&D and photovoltaic manufacturing, notably in China (Van Geenhuizen and Ye 2018). The initial policy enthusiasm for photovoltaics has more recently been extended to the private sector, as a dramatic decline in cost per megawatt for photovoltaic systems has led to increased private sector investment which has raised installed capacity, manufacturing output and R&D expenditure (Masson 2017; REN21 2017).

The innovation trajectory of wind turbines has been towards finding ways to lower operating costs. This is mainly achieved by building fewer but larger turbines, which have higher energy conversion rates, and lower installation and maintenance costs, as compared to a larger number of smaller turbines. Currently the largest installed wind turbine diameter is 160 meter. The 160 meter-diameter wind turbine has a generating capacity of 8-10 MW. Larger diameter wind turbines, in the range of 250 meter, are likely to come to market in the coming years. By contrast in 1987 the largest diameter wind turbine was just 15 meters. Small wind turbines are currently used mainly for off-grid applications, such as in remote rural areas. In addition, research has been devoted to gearless solutions, improved fixation of turbines on the bottom of seas, as well as floating wind turbines. (Kamp, Smits, and Andriesse 2004; International Energy Agency 2016).

More generally, there is an important research challenge concerning the optimization of renewable energy generation systems to ensure that the amount of energy supplied is more stable and aligns better with peak consumption periods. For photovoltaics and wind turbines this means trying to achieve more constant power generation throughout the day, and higher power generation during periods of peak demand, whenever possible. Energy storage, whether using batteries or electrolysis (energy carrier hydrogen), is another part of the solution to match variable supply and demand (International Energy Agency 2016).

A transition to sustainable energy has profound technological, social, economic, and political implications and requires intervention from a large number of different actors (Geels et al. 2011; Geels 2012). The successful adoption of low-carbon technologies depends on the relative power, interests, and policy goals of civil society, media, government (at various levels), political parties, and advisory bodies, in addition to the actions of firm and consumers (Geels et al. 2017). As a result of this complex stakeholder situation, sustainable energy innovation may have a spatial distribution, knowledge network structure, and innovation performance conditions substantially different from those of other high technology sectors.

With regard to location of emergence of some subsectors, one condition specific for sustainable energy is that several types, such as wind energy, sea-based energy (current, tides), solar energy, and biofuels, are often fixed to certain places for optimal production, like windy coasts and mountain ridges, empty desert land, and vast woodlands. These locations are often at a distance from large population centers. The importance of localized natural assets can make smaller towns located nearby attractive locations for R&D and innovation (Van Geenhuizen and Holbrook 2018).

6.2.3 Innovation Actors and Sub-Sector Size

The differences in the sectoral knowledge base of the sustainable energy technology sub-sectors is also evident from an analysis of the main innovation actors. The classification of electric vehicles and wind turbines as sub-sectors with a design and engineering knowledge base appears to be reflected in the lower participation of universities and public research institutions in these sub-sectors (see table D.3, appendix D.2). For electric vehicles and wind turbines 98% of innovation activity (measured by patents) originates from industry and just 2% of innovation activity is from universities. In the other sub-sectors, which are seen as having a scientific knowledge base, there is a more significant presence of university and government research. Universities account for 10% or more of innovation activity in the biofuels, fuel cells, and hydrogen technology sub-sectors, and more than 4% in the electricity storage and photovoltaics sub-sectors, shares between two- and five-times higher than in other sub-sectors. This confirms the existence of closer links to basic scientific research. The results also show that major automotive and automotive parts companies (Toyota, Nissan, Honda, Hyundai, Ford, General Motors, Audi, Robert Bosch) not only appear among the 10 largest patent owners (assignees) for electric vehicles, but also for three other sectors. Electricity storage, fuel cells, and hydrogen technology research all appear to be linked to the automotive industry. In contrast, biofuels, photovoltaics, and wind turbines each appear to have their own distinct group of top innovation actors (see table D.3, appendix D.2).

The differences in size of the sub-sectors should be taken into account when interpreting aggregate sustainable energy technology results. In the descriptive spatial analysis (section 6.3) the aggregate number of sustainable energy patents is used. Approximately 38% of patents are from the electric vehicle and wind turbine sub-sectors, which have a design and engineering knowledge base. The other 62% of patents are from the other scientific knowledge base sub-sectors (2008-2011, see also table D.4, appendix D.2). For parts of the spatial, agglomeration, and knowledge network analysis, and for the cluster innovation performance model, the aggregate number of sustainable energy technology clusters is used. Electric vehicle and wind turbine clusters have a total of 62 clusters (37%) as compared to 105 (63%) for the other sectors (2008-2011, see also table D.4, appendix D.2). The number of clusters is proportional to patent output, and therefore the interpretation of all aggregate sustainable energy technology sector results should take into account the larger share of technology clusters and patents with a scientific knowledge base.

6.3 Cluster Characteristics and Spatial Distribution

This section provides a discussion of the spatial distribution, agglomeration, and knowledge network characteristics of sustainable energy technology clusters. The section is divided into two parts. The first part describes clusters, agglomeration (subsection 6.3.1) and knowledge networks using descriptive statistics (subsection 6.3.2). The second part describes the spatial distribution of the largest, fastest-growing, and newly emerging clusters (subsection 6.3.3).

The results confirm the observation that the sustainable energy technology sector is growing rapidly (see figure 6.1), but they also show that growth is concentrated in specific countries and clusters, with others experiencing a decline in relative terms. Concerning changes at the individual cluster level, San Francisco, Seoul, and Daejeon are rapidly increasing their global share and rank. New cluster formation takes place primarily in the United States followed at a large distance by Germany, Spain, and other countries. While many Asian clusters are growing rapidly, the total number of clusters located in Asia is increasing more gradually.

6.3.1 Clusters and Agglomeration

Spatial concentration brings about agglomeration economies favorable for innovation activity, lowering costs, increasing the quality of services and labor market supply, and facilitating knowledge spillovers. Table 6.1 provides an overview of sustainable energy technology cluster statistics for three four-year periods from 2000-2011. The statistics are subdivided by the *Clusters and Agglomeration* and *Knowledge Networks* headings. The Cluster and Agglomeration indicators are derived from patent counts, which are a measure of innovation activity. The location of patent inventors or their institutional affiliation provides an indication of where innovation activity takes place and which institutions are involved (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004; Squicciarini, Dernis, and Criscuolo 2013). Sustainable energy patents are identified using Y-codes assigned as part of the Cooperative Patent Classification (CPC), a classification jointly developed by the EPO and USPTO (CPC Implementation Group 2017).

The number of sustainable energy patents shows an accelerating trend, with a rise of 3,511 between 2000-2003 and 2004-2007 (+42%) and by 12,375 between 2004-2007 and 2008-2011 (+105%, see also table 6.1). As the sustainable energy technology sector is sensitive to socio-economic changes and policy shifts, such as consumer demand and fiscal incentives favoring the sector, these factors may have influenced the acceleration of sustainable energy patenting activity (Geels 2012; Geels et al. 2017). Despite the rapid increase in patent output, the global distribution of patents across continents remains relatively stable, with 42-43% in Asia, 34-38% in North America 20-21%, in Europe and 1% elsewhere. From the perspective of a "shift to Asia" (hypothesis 1, Dicken (2007)), these results suggest that Asia is the largest producer of sustainable energy technology patents, but that no large shift is taking place.

It is noteworthy that the spatial distribution of patent output from different sub-sectors shows considerable variation: 62% of biofuel patents are from North America, 41% of wind turbine patents are from Europe, and 56% of electric vehicle patents are from Asia, in each case a significantly higher share than the average of the sustainable energy technology sector as a whole (see table C.6, appendix C.3). The total number of sustainable energy technology clusters has also rapidly increased during the study period, rising form 67 in 2000-2003, to 103 in 2004-2007 (+54%), and to 167 in 2008-2011 (+62%). Although all world regions have experienced an increase in sustainable energy technology clusters, the most rapid increase has taken place in Europe, with 6 clusters in 2000-2003, rising to 29 clusters in 2008-2011.

As the number of clusters has increased, so has the share of clustered patents: rising from 36% (2000-2003) to 47% (2008-2011), and showing that most sustainable energy patent output growth is taking place in clusters. This is a trend often observed in sectors that have transitioned from an initial development stage into a high-growth phase (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). Along with the increasing number of clusters, the average size of clusters is also growing, rising from 44.2 patents per cluster (2000-2003) to 67.4 patents per cluster (2008-2011, +52%). There is also variation in the clustering rate and average cluster size among the sub-sectors: in 2008-2011 the clustering rate varied from 27% (electricity storage) to 72% (electric vehicles). Average cluster size ranged from 21.6 patents per cluster (biofuels) to 133.6 (photovoltaics, see table C.6, appendix C.3). The high rate of clustering for electric vehicles fits with its characterization as a sector with an engineering and design knowledge base, in which spatial proximity and interpersonal interaction are seen as playing an important role (Stankiewicz 2002; Asheim and Coenen 2005).

Based on the rising Gini coefficient from 0.66 (2000-2003) to 0.69 (2008-2011), which measures the inequality of cluster sizes, there appears to be a small increase in cluster size inequality. This is likely related to the increasing number of new small clusters at a time when large clusters also experience high growth. The sectors with the greatest concentration (highest Gini coefficient) are electric vehicles (0.74) and photovoltaics (0.64, see table C.6, appendix C.3). Hydrogen technology and wind turbines have the lowest concentration, their Gini coefficients for cluster size are 0.43 and 0.47 respectively. The lower spatial concentration for wind turbines could be related to the importance of localized natural assets, which can make smaller towns attractive locations for wind turbine R&D (Van Geenhuizen and Holbrook 2018) During the same period, corporate patenting has fallen from 93.6% (2000-2003) to 85.8% (2008-2011), which implies that the share of government and university patenting has increased from 6.4% to 14.2% (+122% change). This is a substantial increase in government and university patenting activity, which is understandable given the importance of public policy in the sustainable energy technology sector (Geels 2012; Geels et al. 2017). Corporate patenting is highest in sectors with an engineering and design knowledge base: 95-99.3% for electric vehicles and wind turbines. The sub-sector with the lowest corporate patenting share is hydrogen technology (70.5%).

6.3.2 Knowledge Networks

Doubt about the effectiveness of physical proximity, has moved theoretical attention to “relational” proximity and the importance of knowledge networks, which can involve research collaborations over large distances. Knowledge networks are primarily measured through ratios of the number of network links per cluster or inventor. These network links are derived from co-invention or inventor-assignee relationships. Ratios are used because the size of networks is often dependent on the size and number of network nodes (clusters) (Wasserman and Faust 1994). The rapid growth of clusters and patents during the 2000-2011 period has coincided with the rapid growth of knowledge networks. The growth in the knowledge network appears to be related to the increase in clusters and cluster size, and to more frequent research collaborations between inventors or organizations.

Co-invention links per inventor increased from 0.24 (2000-2003) to 0.32 (2008-2011, +33%), which is a similar trend compared to the increases in the reach and density of network links per cluster. The reach of cluster networks has increased from being linked to just 4.2 different clusters (2000-2003) to 7 different clusters (2008-2011, +67%) on average. The total number of inter-cluster links per cluster (network density) has risen from 7.4 links to 15 links (+103%). The growth of the network and increasing network density is an often observed trend in rapidly growing sectors (Martin and Simmie 2008; Ter Wal and Boschma 2011). Knowledge inflow per inventor (0.58-

0.67), and knowledge outflow per inventor (0.42-0.52) have remained largely stable during the study period.

There is considerable variation in the number of co-invention links per patent in different sub-sectors. This measure varies from 0.18 links per inventor in fuel cells to 0.54 in wind turbines and 0.43 in biofuels (see table C.6, appendix C.3). If knowledge inflow and outflow are seen as a proxy for the level of multinational corporations' research activity in a sector, then wind turbines appears to have the highest penetration (0.87 inflow links per inventor and 0.72 outflow). Low involvement is found in hydrogen technology (0.26 inflow and 0.41 outflow). Relatively large differences in knowledge network indicators in different sectors were noted previously, and partly reflect differences in the innovation process of the sector (Alkemade et al. 2015). The wind turbine sector is also distinct because of its high median co-invention distance at 92 km, more than double the median collaboration distance in the electric vehicle sector (38 km). This difference could be due to the sometimes remote location of wind turbine clusters (Kamp, Smits, and Andriesse 2004; Van Geenhuizen and Holbrook 2018).

Table 6.1: Sustainable energy technology cluster, agglomeration and knowledge network characteristics 2000-2011.

Indicators	2000-2003	2004-2007	2008-2011
Clusters and Agglomeration			
Total patents	8,285	11,796	24,171
- Patents in North America	2,822 (34%)	4,153 (35%)	9,086 (38%)
- Patents in Europe	1,768 (21%)	2,361 (20%)	4,742 (20%)
- Patents in Asia	3,575 (43%)	5,131 (43%)	10,083 (42%)
- Patents in Rest of World	119 (1%)	151 (1%)	260 (1%)
Total Clusters	67	103	167
- Clusters in North America	30 (45%)	49 (48%)	74 (44%)
- Clusters in Europe	6 (9%)	11 (11%)	29 (17%)
- Clusters in Asia	31 (46%)	43 (42%)	62 (37%)
- Clusters in Rest of World	0 (0%)	0 (0%)	2 (1%)
Clustered patents	2,962 (36%)	4,797 (41%)	11,248 (47%)
Patents per cluster, average	44.2	46.6	67.4
Cluster size Gini coefficient	0.67	0.68	0.7
Corporate patenting share	93.6%	89.4%	85.8%
Knowledge Networks (cluster average)			
Co-invention links per inventor	0.24	0.31	0.32
Network reach (unique links per cluster)	4.2	5.4	7
Network density (total links per cluster)	7.4	10.2	15
Knowledge inflow (links per inventor)	0.67	0.58	0.6
Knowledge outflow (links per inventor)	0.42	0.46	0.52
Median co-invention distance (km)	43	45	47

6.3.3 Cluster Spatial Distribution

To increase understanding of the spatial distribution of sustainable energy research, the 10 largest clusters (by patents), newly emerged clusters, and the fastest-growing clusters during the 2000-2011 period are analyzed in this sub-section. Table 6.2 provides an overview of the cities containing the 10 largest clusters during three four-year periods from 2000-2011. The cut-off of 10 clusters is chosen because the share of global innovation output per cluster quickly falls to 1% for the sixth or seventh-largest cluster. Due to the possible measurement uncertainties associated with using patent data, analysis of individual clusters with a 1% share or less, may be based on data that falls within the margin of measurement error.

There are notable shifts among the top-10 clusters during the study period with some fast-rising and some fast-declining clusters. Tokyo and Osaka, in first and second place in 2000-2003 are among the decliners. Although Tokyo maintains first place, its global share of sustainable energy patents declines from 19% to 9% by 2008-2011. Osaka's position falls from second with a 7% share to fifth with a 3% share. Moving upward are San Francisco, Seoul, Daejeon, and Boston. San Francisco rises from fifth position (1% share) to third position (5% share). Seoul rises from seventh position (1% share) to fourth position (4% share). Daejeon and Boston are not among the top-10 clusters in 2000-2003 but appear in seventh and eighth place (1% share) in 2008-2011. These changes suggest that Japan's leading position in sustainable energy research is declining in relative terms, while sustainable energy research in South Korea and the United States are accelerating.

During the 2000-2003 period six of the top-10 clusters are located in Japanese cities, two are in the United States, and one each is located in South Korea and Germany. By 2008-2011 there are four in Japan, three in the United States, one in South Korea and one in Germany. As California, Germany, Japan, and South Korea have seen a history of policy support for sustainable energy initiatives (Vasseur, Kamp, and Negro 2013; Kim 2016; Meckling, Sterner, and Wagner 2017; International Energy Agency (IEA) 2019d), this may explain why many of the largest sustainable energy technology clusters are located there. In many top-10 cities there appears to be a strong presence of electric vehicle patents: most of the top-10 cities also have the headquarters of major automotive companies, including Tokyo (Honda, Nissan), Nagoya (Toyota), Detroit (Chrysler, Ford, General Motors), Seoul (Hyundai Motor), and Stuttgart (Mercedes-Benz, Porsche). Data in table D.3 (appendix D.2) further confirms that many of these firms are also among the largest owners of electric vehicle patents.

The results provide a more nuanced perspective on the observed shift in innovation activity towards Asia noted by Dicken (2007) (hypothesis 1). While the growth of sustainable energy research in Japan appears to be slowing, South Korea and parts of the United States are seeing a rise in sustainable energy research activity. Therefore, there are both intra-Asian shifts in research activity (e.g. from Japan towards South Korea) as well as growth in selected regions outside Asia. This observation is also supported at the country level (see table C.7, appendix C.3), where between 2000-2003 and 2008-2011 the rank and global share of Japan, Germany, Canada, and the United Kingdom is declining, while the United States, South Korea, France, Taiwan, Denmark, and China are rising.

Table 6.2: Cities with 10 largest sustainable energy technology clusters 2000-2011 (share of world sustainable energy patents).

Rank	**2000-2003**	**2004-2007**	**2008-2011**
1	Tokyo, JP (13%)	Tokyo, JP (10%)	Tokyo, JP (9%)
2	Osaka, JP (5%)	Nagoya, JP (7%)	Nagoya, JP (7%)
3	Nagoya, JP (5%)	Osaka, JP (4%)	San Francisco, US (5%)
4	Detroit, US (2%)	Seoul, KR (3%)	Seoul, KR (4%)
5	San Francisco, US (1%)	San Francisco, US (2%)	Osaka, JP (3%)
6	Mito, JP (1%)	Detroit, US (2%)	Detroit, US (2%)
7	Seoul, KR (1%)	Daejeon, KR (1%)	Daejeon, KR (1%)
8	Shizuoka, JP (1%)	Mito, JP (1%)	Boston, US (1%)
9	Utsunomiya, JP (1%)	Munich, DE (1%)	Mito, JP (1%)
10	Stuttgart, DE (1%)	Boston, US (1%)	Stuttgart, DE (1%)

While there is variation in the locations of the largest sub-sector clusters, top-10 sustainable energy technology clusters from different sub-sectors are frequently located in the same cities (see table C.9, appendix C.3). For example Tokyo appears to have top-10 clusters from all sub-sectors, although for biofuels Tokyo is ranked eighth. Osaka (when including nearby Kyoto), Nagoya, Seoul, and Daejeon have clusters from all sustainable transportation related sub-sectors (electric vehicles, electricity storage, fuel cells and hydrogen technology). Osaka and Seoul also have top-10 photovoltaics clusters. However, the biofuels and wind turbine sub-sectors have a different geographical profile, with some top-10 clusters located in smaller cities such as Wilmington in North Carolina, Aurora in Colorado (both biofuel), Aarhus in Denmark, and Greenville in South Carolina (wind turbines). Most of the smaller cities in the sustainable transportation and photovoltaics sub-sectors can be viewed as part of a larger city-region, as they are located near major cities. Examples include Mito, Chiba, and Utsunomiya (near Tokyo), Fremont (near San Francisco), Hsinchu (near Taipei), Princeton and Hartford (near New York, see table C.9, appendix C.3). In this sense the clusters identified in table 6.2 are representative of a broad cross-section of sustainable energy innovation activity, with only biofuels and wind turbines having a notably different spatial distribution. Also noteworthy is that two of the top-10 photovoltaics clusters are in Taiwan, a relatively large number for a comparatively small country, and presumably in part the result of public policy encouraging the development of the sector and the strong local semiconductor industry (Lo, Wang, and Huang 2013).

Newly emerged aggregate sustainable energy clusters are those that did not meet the minimum cluster threshold during the 2000-2003 period, but are identified during the 2008-2011 period. A total of 57 new cities worldwide have newly emerged sustainable energy technology clusters. This includes 32 cities in the United States, seven in Germany, three in Spain, two each in China, Italy and Japan, and one each in Canada, Denmark, Finland, India, Israel, The Netherlands, New Zealand, Singapore, and Taiwan. From the perspective of new cluster formation, it is notable that only eight cities in Asia have newly emerging sustainable energy technology clusters, which suggests that the sustainable energy technology sector has remained more spatially concentrated in this part of the world. This is an observation that confirms earlier research, which noted the high spatial concentration of knowledge resources in large Asian cities, including research universities, public research institutions, and talent (Crescenzi and Rodríguez-Pose 2017). In Europe, Japan, and North America there is generally a greater spatial distribution of innovation activity and resources.

The aggregate growth of clusters is calculated by comparing the 2000-2003 and 2008-2011 periods. The 10 fastest-growing clusters (by patents) are shown in table 6.3. Among them, five are located in Asia, with Tokyo and Nagoya growing by more than 1,000 patents. Among these clusters Seoul has the highest growth rate (+1,409%), followed by Daejeon (+1,151%). Four clusters from the United States are also included, of which the fastest-growing are New York and San Francisco. Berlin is the only top-10 fastest-growing cluster from Europe, and is in sixth place. Rapid growth in sustainable energy research therefore appears to take place not just in Asia, but in a number of cities around the world. Among the slowest growing clusters, only one cluster is experiencing zero growth. Relatively slow-growing clusters are found in Asia (four), North America (five), and Europe (one, see table C.8, appendix C.3).

Table 6.3: Cities with the fastest-growing sustainable energy technology clusters 2000-2011 (absolute growth).

Rank	City	Δ Patents	Rate
1	New York, US	2623	184%
2	Tokyo, JP	1039	160%
3	Nagoya, JP	1025	402%
4	San Francisco, US	1023	1056%
5	Seoul, KR	729	1409%
6	Berlin, DE	486	200%
7	Detroit, US	323	185%
8	Boston, US	220	408%
9	Daejeon, KR	197	1151%
10	Fukuoka, JP	173	66%

6.4 Cluster Innovation Performance

The cluster innovation performance model provides insight into the factors that influence, or are associated with, cluster innovation performance in the sustainable energy technology sector. A brief discussion of the model factors (indicators) is followed by an analysis of the model estimation results. The model contains two different kinds of factors: factors related to the national innovation system and path dependence are seen as "influences" (causality is one-way, towards innovation performance). Factors related to agglomeration and networks are viewed as "associated" with innovation performance, because reverse causalities likely exist (see chapter 3 for a discussion of the research model). An overview of the factors and their indicator values is presented in table 6.4.

Aside from the logarithmic transformation of all model indicators, the cluster size and adjacency indicators have also undergone a 10^{-5} transformation to ensure that their estimated model coefficients are in a similar range compared to the other indicators. As a result, the indicator range for cluster size and adjacency appear to be relatively small. The national innovation system indicator tends towards higher values. This is because a large number of clusters is located in high-quality innovation systems such as the United States, Switzerland, and Japan (Schwab and Sala-i-Martin 2015). The national innovation system indicator is a composite indicator based on research investment, the quality of the higher education system, university-industry collaborations and protection of intellectual property.

The knowledge base of the two sub-sectors is accounted for in the model using a dummy variable, which indicates whether a cluster has an engineering and design knowledge base (photovolatics and wind turbines). The implementation and testing of the model is described in detail in section 3.6.2 and 3.6.3 (chapter 3). The model estimation results are within the accepted boundaries for multicollinearity (Variance Inflation Factor < 2) and normally distributed residuals (Shapiro-Wilk test $p < 0.10$). However, heteroscedasticity is not within the accepted boundaries for most model estimations (Breusch-Pagan $p < 0.10$). Heteroscedasticity issues mean that the values of the coefficients may be biased, although this does not appear to influence the statistical significance of correlation in a meaningful way (Lumley et al. 2002; Meuleman, Loosveldt, and Emonds 2015).

Therefore, the basic assumptions of Ordinary Least Squares (OLS) regression are being met and the correlations in the model results are robust. As is the case for the health technology sector, an OLS regression is also used for an initial exploration of the correlation and associations between various indicators in the sustainable energy technology sector.

Table 6.4: Statistical summary of sustainable energy technology model indicators (log-transformed, $n = 167$).

Indicator	**Measurement**	**Minimum**	**Mean**	**Maximum**
Innovation performance, IVP	Patent citations	-2.30	0.398	3.61
Cluster size, PAT	Patent count	-2.30	-2.30	-2.19
Adjacency, ADJ	Patent count	-2.30	-2.28	-2.06
Regional specialization, SPE	Patent count	-2.30	-2.11	-0.152
Corporate research, CRP	Patent assignees	-2.30	-0.133	0.0953
National innovation system, NSQ	Composite indicator*	1.22	1.66	1.73
Knowledge inflow, MNC	Patent inventor-assignee network	-2.30	-0.875	1.92
Knowledge outflow, LAB	Patent inventor-assignee network	-2.30	-0.718	0.936
Network reach, NET_S	Patent co-invention network	-1.61	-0.429	1.34
Network density, NET_W	Patent co-invention network	-2.06	-1.06	0.910
Past innovation performance, IVP_P	Patent citations (previous period)	-2.30	1.45	3.96

* Composite indicator of national private and public sector research investment, quality of higher education system, university-industry collaborations and protection of intellectual property.

The model estimation results in table 6.4 are discussed below. The **agglomeration model** consists of two scale-based agglomeration indicators (cluster size PAT and adjacency ADJ), a diversity-based agglomeration indicator (specialization SPE), and a qualitative agglomeration indicators which describe the presence of corporate research (CRP). The partial models' predictive power is expressed by an adjusted ΔR^2 of 0.159.

The scale-based indicators measure the number of patents produced inside the cluster (cluster size) and the number of patents produced within other clusters of the same sub-sector located within 200 km of the cluster (adjacency). Cluster size has a positive and statistically significant association with cluster innovation performance, but there is no statistically significant association with adjacency. Regional specialization is a measure of sectoral cluster patenting relative to patenting from *all* other sectors within the cluster's geographic boundaries. Regional specialization is statistically significant and is positively associated with cluster innovation performance in sustainable energy technology clusters. The benefits of specialization can be attributed to a better match with specific needs for high-quality labor, services, and specialized learning (Giuliano, Kang, and Yuan 2019). Corporate research measures the share of cluster patents owned by private sector corporations. Corporate research has no statistically significant association with the dependent variable. The agglomeration model estimation results provide support for hypothesis 3 (economies of scale) and hypothesis 4 (specialization).

The **national innovation system model** has one independent variable: national innovation system quality (NSQ). National innovation system quality is a composite measure that incorporates private and public sector research investment, quality of higher education system, university-industry collaborations and protection of intellectual property at the national level. National innovation system quality has a positive and statistically significant influence on cluster innovation performance. The predictive power (adjusted ΔR^2 of 0.164) is comparable to that of the agglomeration model. The quality of the national innovation system therefore appears to positively influence cluster innovation performance, and as a result hypothesis 6 (national innovation system) is not rejected.

The **knowledge network model** encompasses two indicators related to knowledge inflow (MNC) and knowledge outflow (LAB), and two indicators related to the cluster's position (degree centrality) in the inter-cluster knowledge co-invention network (NET_S and NET_W). The knowledge flow indicators are derived from the inter-cluster inventor-assignee network, with an outbound inventor-assignee link indicating knowledge outflow and an inbound link indicating inflow. Both knowledge flow indicators and the weighted degree centrality indicator are divided by the number of inventors.

The partial models' predictive power is an adjusted ΔR^2 of 0.205, which is slightly more than the predictive power of the agglomeration and national innovation system models described before. Only one knowledge network indicator is statistically significant: network reach. Network reach has a positive association with cluster innovation performance, enabling the cluster to access a greater diversity of specialist knowledge (Bathelt, Malmberg, and Maskell 2004). Knowledge inflow and network density also appear to have a positive association with cluster innovation performance, but their statistical significance falls just below the 90%-threshold. The positive association of network reach provides support for hypothesis 9 (network reach).

Next, the **path dependence model** is estimated using only one indicator: past innovation performance (IVP_P). Past innovation performance is calculated from patent data of the preceding 2004-2007 period. In the sustainable energy technology sector past innovation performance has a relatively low correlation with the dependent variable (R^2 of 0.28, see the correlation matrix, table B.12, appendix B.3). In the model estimation past innovation performance has a positive and statistically significant association with cluster innovation performance. The model's predictive power is an adjusted ΔR^2 of 0.243 which is the highest explanatory power of all partial models. The path dependence model result provides support for hypothesis 11. Hypothesis 11 suggests a positive influence of past innovation performance on current innovation performance. Clusters (and organizations) that have performed well in the past tend to continue to do well due to the accumulation of knowledge, experience, skills, trust, reputation, etc. (Boschma and Frenken 2006; Crescenzi and Rodríguez-Pose 2011; Vergne and Durand 2011; Trippl et al. 2015; Crescenzi and Jaax 2017).

The final partial model includes indicators of two previously discussed partial models, namely, *agglomeration and knowledge network* models, as well as the national innovation system model described earlier. To avoid issues of multicolinearity the network reach indicator is excluded from the model estimation (see also table B.12, appendix B.3). The model estimation results of the agglomeration and network model are similar to those of the earlier partial models, except that regional specialization falls just below the 90% statistical significance threshold, while the statistical significance of the network density indicator rises to 95%. The network density indicator is positive, suggesting that a dense knowledge network supports higher innovation performance, or if the causality is reversed, that clusters with high innovation performance are able to establish dense knowledge network. The model's predictive power is an adjusted ΔR^2 of 0.200, which is higher than that of the agglomeration model, but slightly lower than the knowledge network model. This difference can be explained by the exclusion of network reach from the combined model estimation.

Table 6.5: Sustainable energy technology cluster innovation performance model estimation results 2008-2011.

Indicators	**Control**	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration and Network**
Cluster size		7.0 (2.9)**				8.9 (3.5)**
Adjacency		-1.7 (1.2)				-1.7 (1.2)
Regional specialization		0.36 (0.20)*				0.32 (0.20)
Corporate research		0.048 (0.15)				0.00097 (0.15)
National innovation system			1.1 (0.46)**			0.88 (0.49)*
Knowledge inflow				0.11 (0.072)		0.12 (0.075)
Knowledge outflow				-0.098 (0.14)		-0.11 (0.13)
Network reach				0.27 (0.12)**		
Network density				0.17 (0.12)		0.29 (0.13)**
Past innovation performance					0.31 (0.077)***	
Knowledge base (dummy)	-2.3 (0.66)***	-0.96 (0.15)***	-1.1 (0.13)***	-1.0 (0.13)***	-0.71 (0.15)***	-0.99 (0.15)***
Constant	3.9 (0.63)***	14. (7.3)*	-0.78 (0.73)	1.4 (0.16)***	0.43 (0.19)**	17. (8.9)*
Adjusted R^2	0.091	0.250	0.254	0.296	0.334	0.292
Adjusted ΔR^2		0.159	0.164	0.205	0.243	0.201
Clusters (n)	167	167	167	167	167	167

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

From an evolutionary perspective, agglomeration, and knowledge networks develop and accumulate over time, for this reason they can also be seen as part of a cluster's path dependence. As a rough estimate of their impact, the predictive power of the agglomeration and knowledge network models can be compared to that of the path dependence model. In the sustainable energy technology sector the knowledge network and agglomeration factors appear to account for between 65% and 84%[1] of the predictive power of the path dependence model. Other factors such as knowledge, skills, reputation, experience, and specialized resources likely account for the remainder of the path dependence model's predictive power, along with agglomeration and network effects not measured by the indicators used in this study (Simmie and Strambach 2006; Martin and Simmie 2008). Because the sustainable energy technology sector is in an early development stage and experiencing exponential growth, the importance of non-network and non-agglomeration factors appears smaller (possibly as low as 16%) when compared to the more mature health technology sector, where non-network and non-agglomeration factors account for as much as 53% of path dependence (see chapter 5).

When the aggregate sustainable energy technology model estimation results are compared to those of the science-based sub-sectors (see table B.13, appendix B.3) and the engineering and design-based electric vehicle and wind turbine sub-sectors (see table B.14, appendix B.3) there are some notable differences. In sub-sectors with a scientific knowledge base, knowledge networks appear to have a stronger and positive association with cluster innovation performance. On the other hand, in sub-sectors with an engineering and design knowledge base, the national innovation system has a relatively strong and positive influence, while knowledge networks appear to have a negative association with cluster innovation performance. This suggests a strong and positive national influence in these sectors, relative to the stronger global-network influence in science-based sectors. These patterns fit with the understanding that knowledge in design and engineering-based sectors is more tacit and relies more on interpersonal interactions, which are facilitated by close spatial proximity. This, in contrast to science-based sectors, where more codified knowledge facilitates knowledge transfers and collaboration over long distances (Stankiewicz 2002; Asheim and Coenen 2005).

6.5 Discussion

This section provides an analysis of the results from this chapter and their theoretical implications. The section begins with an evaluation of the relevant hypotheses and is followed by a further discussion of some additional observations. A total of 10 hypotheses are evaluated based on the empirical results of this chapter (see table 6.6).

Hypothesis 1 addresses the spatial distribution of sustainable energy technology clusters and posits that new and fast-growing clusters are *mainly* located in Asia. Such a pattern is rejected by the analysis for a number of reasons. First, Asia already has a strong position in sustainable energy R&D, accounting for 42% of global patent output since the beginning of the 2000-2011 study period. Second, while new clusters and fast-growing clusters are found in Asian countries such as Japan and South Korea, new and fast-growing clusters are also found in a number of other countries such as the United States and Germany. In this sense any "shift" to Asia has already

[1] calculated by adding the adjusted ΔR^2 values of the agglomeration and knowledge network models and dividing by the path dependence model.

occurred and is not unique to Asian countries. Both countries in Asia and elsewhere see a decline in relative terms (including Japan, Germany, and the United Kingdom) while others are rising (including the United States, South Korea, and France).

Agglomeration is addressed by way of hypotheses 3-5. Hypothesis 3 covers scale-based agglomeration. Hypothesis 3 is not rejected because cluster size is positively associated with cluster innovation performance. This suggests that there are advantages of spatial proximity, such as increased opportunities for collaboration and knowledge spillovers (Morgan 2004; Capello 2009). Note that there is no statistically significant adjacency effect. Hypothesis 4 posits that regional specialization has a positive effect, and this is not rejected by the results. The results suggest that local inter-sectoral knowledge spillovers may be of limited importance in the sustainable energy technology sector, and that sustainable energy technology clusters can develop successfully in smaller cities (Camagni and Capello 2002; Capello 2009; Giuliano, Kang, and Yuan 2019).

Hypothesis 5 claims a positive relationship between corporate research activity and cluster innovation performance: this relationship is rejected. This outcome fits with the observed decline of the corporate research share of sustainable energy research and the increase in university and public sector research (see table 6.1. This increase is likely related to the sector's role in socio-technological transitions, which are an important policy focus (Geels 2012; Geels et al. 2017). Hypothesis 6, which suggests that the national innovation system has a strong influence on cluster innovation performance, is not rejected by the empirical results.

Hypotheses 7-10 are concerned with knowledge networks. Hypotheses 7 and 8 cover knowledge inflow and knowledge outflow and they are rejected. Hypothesis 9 and 10 address the knowledge network structure. The empirical results show a positive relationship between network reach and cluster innovation performance (hypothesis 9). The positive influence of network density in cluster innovation performance appears not rejected in the agglomeration and knowledge network model (hypothesis 10), a model where network reach is excluded. Taken together, the results highlight the positive role of knowledge networks (research collaboration) in sustainable energy technology clusters.

Hypothesis 11 proposes that path dependence positively influences cluster innovation performance, and this view is not rejected by the empirical results. The result fits with the theoretical expectations that cluster innovation capabilities accumulate over time, whereby relatively young clusters (and organizations) that have done well historically, tend to continue to do well due to the accumulation of resources and other advantages (Boschma and Frenken 2006; Crescenzi and Rodríguez-Pose 2011; Vergne and Durand 2011; Trippl et al. 2015).

Table 6.6: Evaluation of hypotheses for the sustainable energy technology sector.

Hypotheses	**Evaluation**
Hypothesis 1: New and fast-growing sustainability technology clusters are more frequently located in Asia.	Rejected
Hypothesis 3: Agglomeration has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 4: Regional specialization has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 5: Corporate research activity has a positive association with cluster innovation performance.	Rejected
Hypothesis 6: The quality of the national innovation system has a positive influence on cluster innovation performance.	Not Rejected
Hypothesis 7: Knowledge inflow has a positive association with cluster innovation performance.	Rejected
Hypothesis 8: Knowledge outflow has a positive association with cluster innovation performance.	Rejected
Hypothesis 9: The reach of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 10: The density of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Not Rejected
Hypothesis 11: Past cluster innovation performance has a positive influence on current cluster innovation performance.	Not Rejected

The empirical results presented above support the view that the sustainable energy technology sector is in a *path creating* phase and this path creating process is further influenced by the role of the sector in the socio-technological transformation towards a low-carbon energy system (Ter Wal and Boschma 2011; Martin and Simmie 2008; Geels et al. 2011; Geels 2012).

From a spatial perspective, the creation of new sustainable energy technology clusters during the study period in locations around the world is a clear indicator of spatial path creation (Ter Wal and Boschma 2011). From an innovation cluster performance perspective the predictive power of the sustainable energy technology path dependence model is also relatively low (ΔR^2 of 0.243) when compared to the stable health technology sector which is in a mature development (ΔR^2 of 0.486), thus the path dependence of innovation performance in the sustainable energy technology sector seems notably weaker. The increased presence of university and government actors in sustainable energy research is also more characteristic of a sector in an early development stage (Ter Wal and Boschma 2011; Isaksen 2016). As sectors develop the share of corporate research tends to increase, although the opposite trend is visible in the sustainable energy technology sector during the 2000-2011 study period.

During a sector's path creation stage there is a great deal of uncertainty concerning the technological path to be chosen and their social and political acceptance. High innovation performance, as measured by the number of patent citations per inventor, can be significantly influenced by economic and policy choices, rather than by the "pure" innovation performance of researchers, as would be the case in other sectors. In sectors with a stable technological trajectory agglomeration, knowledge networks and path dependence are likely to play a more prominent role (Martin and Simmie 2008; Ter Wal and Boschma 2011). Amid this evidence of path creation, there is also strong spatial path dependence as cities in Japan and South Korea, as well as San Francisco, have top-10 clusters from 5 or more sustainable energy technology sub-sectors. While the results do not suggest that the concentration of multiple sustainable energy technology sub-sectors within one city is associated with higher innovation performance, it is nevertheless a notable spatial phenomenon.

6.6 Conclusion

This chapter has provided an overview of the spatial distribution, knowledge networks, and the characteristics associated with cluster innovation performance in the sustainable energy technology sector. The analysis has revealed a number of knowledge gaps related to the changing spatial distribution of sustainable energy technology innovation and the lack of support for a number of hypotheses. Both could be related to the sector's path creating development phase and the influence of public policy in view of the sector's role in a broader socio-technological energy sustainability transition (Ter Wal and Boschma 2011; Geels 2012). With regard to its spatial distribution, there appears to be a complex growth pattern as almost all sustainable energy technology clusters are growing, and many new sustainable energy technology clusters are being created in multiple countries. These countries range from innovation leaders such as the United States, to countries with more modest innovation capabilities such as Spain and India (Schwab and Sala-i-Martin 2015). However, the growth and formation of new sustainable energy technology clusters is unbalanced, with clusters within the same country, or countries within the same region, showing both relatively high, and relatively low growth. A likely explanation for this mixed spatial picture is the path creation phase of the sector and government policies which support sustainable energy technology development. As a technological path is still being created, governments may target certain cities and technologies to support, but there is also great uncertainty in the eventual technological and economic outcomes (Martin and Simmie 2008). For example, the growth of Denmark in sustainable energy research is likely related to the rapid growth of the wind turbine sub-sector (Nielsen 2017). The city of Daejeon in South Korea is targeted for sustainable energy research by the national government (Wu 2014; Jeong 2017). This technological and policy complexity appears to be reflected in the spatial distribution patterns of the sector's growth.

With regard to the higher number of hypotheses rejected in the sustainable energy technology sector compared to the health technology sector, this can also be attributed to the sector's developmental and socio-technological context. The role of corporate research and knowledge flows, which are typically facilitated by multinational corporations, are not statistically significant, while there is a statistically significant relationship with the national innovation system. This suggests that the role of the corporate sector and multinational corporations may be smaller, while the role of government is greater, further emphasizing the role of policy makers and other actors in socio-technological transitions.

In the next chapter (chapter 7) the results of this chapter and the previous chapter are compared and benchmarked against reference high technology sectors. This is done to identify which patterns and cluster characteristics are specific to each sustainability technology sector, and which factors influence all high technology clusters.

Chapter 7

Comparative Analysis of Sustainability Technology Sectors and Policy Relevance

7.1 Introduction

This chapter offers a comparison of the sustainability technology sectors against a benchmark of other high technology sectors and a discussion of the policy implications of the research. The chapter begins with a sectoral comparison aimed at better understanding how the sustainability technology sectors' knowledge base, development phase and involvement in socio-technological transitions influences the spatial distribution, knowledge networks, agglomeration patterns and the factors associated with cluster innovation performance (Ter Wal and Boschma 2011; Binz and Truffer 2017; Geels et al. 2017; Steen and Hansen 2018). Certain cluster characteristics and spatial patterns occur, or are important, only in a specific sector or development phase. As a result, these differences can provide new insights into the sector and its underlying innovation process. The reference high technology sector, with which the sustainability technology sectors are compared, combines the aerospace, biotechnology, chemicals, electronics, defense, electrical equipment, machinery and equipment, motor vehicles and pharmaceuticals technology clusters. The spatial patterns and cluster characteristics of these sectors represent an aggregate benchmark of the high technology sector (OECD 2013; Galindo-Rueda and Verger 2016).

The second part of the chapter describes a preliminary framework of cluster innovation strategies and provides a discussion of how these strategies relate to the cluster innovation performance research results, which are summarized and analyzed in the first part of the chapter. The framework is based on a regional policy and evolutionary perspective (Njøs and Jakobsen 2016) and includes notable counter-examples of strategies for technological catch-up that were observed in certain Asian countries (Lee 2016).

The changing global spatial distribution, agglomeration and knowledge network structure of the sectors is compared first (section 7.2). This is followed by a comparison of the factors that influence, or are associated with, cluster innovation performance (section 7.3). These results, together with the relevant hypotheses are evaluated in section 7.4. The policy relevance of the research findings are discussed next (section 7.5), and a brief conclusion of the chapter is presented at the end (section 7.6).

7.2 Changes in Cluster Characteristics and Spatial Distribution

The cluster characteristics of a sector tend to reflect different aspects of its innovation processes. For example, Carlsson (2013) observes that in sectors where tacit knowledge and inter-personal interactions are important in innovation processes, innovation actors can benefit from close spatial proximity (agglomeration). Ter Wal and Boschma (2011) note that agglomeration and the density of knowledge networks increase as clusters mature. The comparative quantitative analysis of cluster characteristics in this chapter allows sectoral differences to be examined more closely, including differences in the clustering rate and global spatial shifts in technology clusters and patent output. The cluster characteristics presented in table 7.1 cover the sectors' size (in terms of patents and clusters) and other indicators that help to differentiate between the sectors. These indicators are selected based on differences in their average value or changes in their value (growth, decline) between 2000-2003 and 2008-2011. The sustainability technology sectors are compared with each other and with the high technology reference sector[1].

As discussed in earlier chapters, the sustainable energy technology sector is growing rapidly. Its patent output increased by 192% and the number of clusters by 149% between 2000-2003 and 2008-2011. This is very different from the 2-5% growth over the same period for health technology. The rapid growth of sustainable energy technology also affects other cluster indicators: there is a 31% increase in the number of clustered patents and a 5% increase in the cluster size Gini coefficient, which shows increasing agglomeration. To be specific, a rising Gini coefficient indicates increasing inequality in cluster size (large clusters are growing faster than smaller clusters). A 33% rise in co-invention links per inventor shows that the sector's knowledge network is becoming denser. These observations fit the spatial pattern of a sector transitioning from an emerging to a mature development phase (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015).

Despite the rapid growth of the sustainable energy technology sector, during 2008-2011 many of its cluster characteristics appear to be similar to those of the reference high technology sector. The sector's corporate research share at 85.8% is similar to the reference of 88.6% (Welch t-test $p > 0.19$, see Delacre, Lakens, and Leys (2017)). The sectors 0.32 co-invention links per inventor is almost the same as the reference value of 0.36 (Welch t-test $p > 0.11$). Eventhough these indicators suggest some similarity between the sustainable energy technology sector and the reference high technology sectors, Persoon, Bekkers, and Alkemade (2020) conclude that sustainable energy technology builds more on recent and diverse scientific research than traditional (fossil fuel) energy technologies.

When observing the same cluster indicators for the health technology sector, they deviate from the reference values in a significant way, with corporate research share at 73.4% and co-invention links at 0.41 (for both Welch t-test $p < 0.001$). A lower share of corporate research and more frequent inter-cluster knowledge links fits with the sector's characterization as being more science-based. Science-based sectors are known to have higher participation by university and government actors and relatively frequent long-distance research collaboration because knowledge is more easily codified and transmitted (Owen-Smith et al. 2002; Alkemade et al. 2015; Binz and Truffer 2017).

The sustainable energy technology and health technology sectors have very similar clustering rates (42-47%) and Gini coefficients (0.67-0.69), which are both lower than the reference values. Given the stability of the health technology sector, it appears that a lower clustering rate and more

[1]The selection of the reference high technology sectors is discussed in section 3.4 of chapter 3.

equal distribution of cluster size are a constant feature. However, the increasing trend for both indicators in sustainable energy technology suggests that the sector could become more similar to the reference high technology sector in future. Both sectors also show a falling share of corporate research (-3% to -8%), which suggests a corresponding increase in university and government R&D. It is conceivable that this increase is being driven by growth in public R&D expenditure within the context of the sectors' role in socio-technological transitions. Within the context of the sustainable energy sector, public policies and R&D expenditure are enhanced by the Kyoto protocol (adopted in 1997) and its later enforcement. The default expectation is that a sectors corporate research expenditure gradually increases as a new technology becomes economically viable due to customer acceptance (Ter Wal and Boschma 2011; Mohr, Sengupta, and Slater 2013).

In sum, the results do not provide strong support for hypothesis 2, which posits that the health technology sector has a denser knowledge network and is more clustered than the sustainable energy sector. Eventhough the health technology sector clearly has a much denser knowledge network, its clustering rate (agglomeration) at 42%, is somewhat lower than the 47% clustering rate of the sustainable energy sector. The lower clustering rate of health technology appears to be mainly due to the very low clustering rate of medical devices (see chapter 5).

Table 7.1: Technology sector comparison of selected cluster statistics during the 2008-2011 period.

Indicators	**Healthcare**	**Sustainable Energy**	**Reference**
Total patents	72,051 (+5%)	24,171 (+192%)	743,466
Total clusters	219 (+2%)	167 (+149%)	1,192
Clustered patents	42% (-11%)	47% (+31%)	72%
Cluster size Gini coefficient	0.67 (no change)	0.69 (+5%)	0.84
Corporate research share	73.4% (-3%)	85.8% (-8%)	88.6%
Co-invention links per inventor	0.41 (+8%)	0.32 (+33%)	0.36

Note: Change (%) between 2000-2003 and 2008-2011 in parentheses.

When comparing the cities with the 10 largest clusters of each sector, there is a high degree of overlap between the health technology and aggregate high technology sectors (eight cities). By contrast only five of the 10 largest sustainable energy technology clusters are located in the same cities as the largest reference high technology clusters (see also table C.12, appendix C.4). This difference suggests that specific factors influence the creation and growth of large sustainable energy technology clusters. For example, and as discussed earlier in chapter 6, some of the largest sustainable energy technology clusters are located in cities with a large automotive industry, such as Nagoya, Detroit and Stuttgart. This co-location phenomenon makes sense given the strong links between the automotive industry and research into electric vehicles and electricity storage. Therefore, large sustainable energy technology clusters appear to have been created in these specific cities because of investment by the automotive industry based there. There is also an emergence of smaller clusters outside large metropolitan areas, derived from traditional manufacturing and (fine-mechanical) skills like in the production of medical devices, or derived from the availability of natural assets in remote areas (different sources of non-fossil energy) (Klein, Banga, and Martelli 2015; Van Geenhuizen and Holbrook 2018).

7.3 Cluster Innovation Performance

Comparing cluster innovation performance and the associated cluster characteristics across different sectors provides insight into the relative *importance* of these characteristics in explaining differences in innovation performance. The comparative analysis takes the reference high technology sector as a starting point, with which the health technology and sustainable energy technology sectors are compared. The analysis below is divided into four parts, which follow the four main partial models: agglomeration, national innovation system, knowledge networks and path dependence. A summary of the model estimation results, on which the comparative analysis is based, is presented in table 7.2 and table 7.3 below. Full model estimation results for the reference high technology sector are presented in appendix B.4.

In the reference sector and the health technology sector, cluster size, regional specialization and corporate research are positively associated with cluster innovation performance, and adjacency of clusters negatively; all factors are statistically significant (hypothesis 3 is partially rejected; hypotheses 4 and 5 are not rejected). However, in the sustainable energy technology sector the associations of adjacency (negative) and corporate research (positive) are *not* statistically significant. The negative association of adjacency can be seen as part of negative economies of scale, which appear to act on a regional scale (< 200 km) but not within the local cluster. Negative economies of scale might arise due to competition for talent, customers and resources from other same-sector clusters located nearby (Martin and Sunley 2003), but such competition does not appear to play a significant role in core sustainable energy technology clusters. On the other hand, a positive association of corporate research suggests that a cluster needs a sufficient number of capable local firms that absorb the benefits of knowledge spillovers from universities and publicly-funded research and translate these into strong innovation strategies and R&D (Teece, Pisano, and Shuen 1997; Capello 2009; Qiu, Liu, and Gao 2017), but the model estimation results suggest that this is not a significant factor in explaining the innovation performance of sustainable energy technology clusters. An explanation for the absence of an adjacency effect could be the emerging development phase of the sector, due to which negative economies of scale have not yet taken hold, leading back to some of the cluster emergence outside large metropolitan area. An explanation for the apparently smaller importance of corporate research could be related to the role that other actors play (government, civic organizations, etc.) in socio-technological transitions in the energy sector (Geels 2012; Geels et al. 2017).

The national innovation system (hypothesis 6) only has a statistically significant influence in the sustainable energy technology sector, suggesting that this sector is more sensitive to national policies promoting renewable energy research and adoption (Langhelle, Meadowcroft, and Rosenbloom 2019). This is particularly important since the adoption of the Kyoto Protocol (1997) and its enforcement, and the design of national and regional policies that followed. In the other sectors the influence of national policies appear to be weaker or less direct, presumably due to the stronger influence of globalization (Strange 1996; Binz and Truffer 2017).

Further, knowledge inflow and outflow, often facilitated by multinational corporations, are positively associated with cluster innovation performance in the reference sector (hypotheses 7 and 8 not rejected). The positive association can be seen as a result of multinational corporations establishing remote labs in already successful clusters (De Propris and Driffield 2005; Østergaard and Park 2015). However, this phenomenon is notably absent in the sustainable energy technology sector, which signals a modest role of multinational corporations in the sector, a phenomenon that could be related to the sector's emerging development phase, during which dominant multinational corporations have not yet established themselves (Ter Wal and Boschma 2011; Awate, Larsen, and Mudambi 2015; Binz et al. 2017). Returning to the reference sector, there is a *negative* association with the other two knowledge network indicators, network reach and density (hypothesis 10 rejected). With regards to network density, this result can be seen as a saturation effect: beyond a certain number of linkages, the cost of maintaining external network linkages may divert resources from the internal network linkages in the cluster or exceed the cluster's own absorptive capacity (Ye, Yu, and Leydesdorff 2013; Lau and Lo 2015; Tomás-Miquel, Molina-Morales, and Expósito-Langa 2019), however this is not (yet) the case in the sustainability technology sectors. Network reach is generally considered to be positive (hypothesis 9), which is the case in both the sustainability technology sectors and also for science-based part of the reference high technology sector (table B.18, appendix B.4), but not for the reference high technology sector as a whole (table B.17, appendix B.4).

Table 7.2: Technology sector comparison of cluster innovation performance factors and direction.

Factor	**Healthcare**	**Sustainable Energy**	**Reference**
Cluster size	+***	+**	+***
Adjacency	-***	-	-***
Regional specialization	+**	+*	+***
Corporate research	+***	+	+***
National innovation system	-	+***	+
Knowledge inflow	+	+	+***
Knowledge outflow	+***	-	+***
Network reach	+***	+**	-***
Network density	-	+	-***
Past innovation performance (path dependence)	+***	+***	+***

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Past cluster innovation performance (path dependence), like including effects from cluster size and regional specialization, has a positive and statistically significant influence on cluster innovation performance in all three sectors. This suggests that all three sectors are in a path dependent development phase, in which cluster capabilities are accumulated over time (Martin and Simmie 2008), although the strength of path dependence varies. Table 7.3 shows that the explanatory power of the path dependence model is notably stronger for the reference and healthcare sectors (R^2 of 0.560 and 0.490) than in the sustainable energy technology sector (R^2 of 0.334, hypothesis 12 is not rejected). In all other model estimations except path dependence, the model explanatory of the sustainable energy technology sector exceeds that of the other two sectors. This observation fits with the findings of Ter Wal and Boschma (2011), who note based on an extensive literature review, that agglomeration and knowledge networks play a (more) important role in the emerging development phase of a sector. If the agglomeration and knowledge networks model is taken as an example, sustainable energy technology's explanatory power (R^2 of 0.291) exceeds that of the healthcare and reference sectors by a wide margin (R^2 of 0.121 and 0.187).

Aside from the different circumstances of the sustainable energy technology, which the model explanatory power clearly illustrates, it is notable that in the health technology sector *knowledge* *networks* have a relatively high explanatory power. However, in the reference high technology sector *agglomeration* is stronger than knowledge networks. This difference can be attributed to the low clustering share (low agglomeration) and high number of co-invention links per inventors (large network) in the health technology sector when compared to the reference values (see table 7.1 earlier). Yet dense networks and a high rate of agglomeration, as shown by the sustainable energy technology sector, do not automatically mean that these factors are the most important to cluster innovation performance.

The picture that emerges from the comparative analysis of cluster innovation performance is two-fold. On the one hand the sustainable energy technology sector closely follows the agglomeration and knowledge network patterns of an emerging sector. The health technology sector is more mature, and more similar to the reference sector. On the other hand the health technology sector shows some notable differences from the reference sector, which seem related to its knowledge base.

Table 7.3: Technology sector comparison of cluster innovation performance partial-models explanatory power (R^2).

Factor	**Health Technology**	**Sustainable Energy**	**Reference**
Agglomeration	0.091	0.249	0.176
National innovation system	-0.001	0.254	-0.001
Knowledge networks	0.143	0.296	0.040
Path dependence	0.490	0.334	0.560
Agglomeration and knowledge networks	0.121	0.291	0.187

7.4 Comparison of Sustainability Technology Sectors

Whereas the preceding analysis has focused on comparing the sustainability technology sectors to the reference sector, this section compares the sustainability technology sectors with each other. The comparison is made from the perspective of socio-technological transitions. These transitions are geographically bounded, requiring a supportive local environment to succeed (Truffer, Murphy, and Raven 2015). The transitions are also influenced by many different actors: aside from knowledge producers, firms and consumers, civil society, media, government, regulators, investors, political parties and advisory bodies often play an important role (Geels et al. 2017). A comparison between the sustainability technology sectors is made based on the hypotheses about cluster innovation performance (table 7.4) and sectoral differences (table 7.5).

Concerning agglomeration, hypotheses 3 is partially rejected. Local agglomeration is associated with innovation performance, while regional agglomeration (through adjacent clusters) has a negative association, or is not significant, as is the case for sustainable energy technology clusters. The negative association with regional agglomeration signal the presence of diseconomies of scale, whereby at a regional level (up to 200 km) there appears to be greater competition or higher cost for talent and other knowledge resources if a cluster is located near another large cluster from the same sub-sector. In the case of sustainable energy technology clusters such diseconomies of scale may be less relevant because they depend more on local support from their own cluster (such as subsidies, innovation projects or university research), possibly making interactions with nearby sustainable energy technology clusters less important. On the other hand, the health technology sector does show diseconomies of scale caused by nearby health technology clusters. This situation could be due to the health technology sector's strong path dependence (hypothesis 12), which may make its technological innovation more competition-driven, as researchers innovate within a more clearly established technological development trajectory (Martin and Simmie 2008).

Hypothesis 3 (agglomeration), along with hypotheses 4 (regional specialization) and 11 (path dependence) are accepted for all sectors, which implies that these factors are not sector-specific. However, it must be noted that the strength of agglomeration and path dependence varies as shown in table 7.3 and discussed in section 7.3. With regard to regional specialization, it is known that some prominent sustainable energy technology and health technology clusters are located in smaller towns or cities (Ó hUallacháin and Lee 2014; Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Ye 2018), a situation that leads to a high degree of regional specialization. The model estimation results suggest that in all sectors such regional specialization is associated with high cluster innovation performance. Within the European Union this development can be seen as a precursor of a "smart specialization strategy" in regional innovation policy, in which the focus is strongly on specific regional assets, including natural assets, or advantages originating from previous industrial paths, like skills in fine-mechanics and metal work (McCann and Ortega-Argilés 2015; Morgan 2017; Steen, Faller, and Fyhn Ullern 2019).

The share of corporate research (hypothesis 5) is seen as a proxy for a cluster's absorptive capacity and ability to transform knowledge into competitive strategies, but is not statistically significant in the sustainable energy technology sector. A smaller role of corporate research fits from the perspective of socio-technological transitions because many different actor types influence the socio-technological innovation and transformation process (Geels et al. 2017). Corporate research is statistically significant in the health technology sector even though the share of corporate research in health technology clusters is significantly lower than in other sectors. This situation can be attributed to the scientific knowledge base of the health technology sector and the close links to research at universities and (academic) hospitals (Gelijns and Thier 2002). In this sense the relationship between corporate research, socio-technological transitions and innovation performance appears more complex.

In contrast to corporate research, the national innovation system (hypothesis 6) *is* a statistically significant factor in sustainable energy technology clusters. This suggests that clusters located in highly innovative countries such as the United States, Finland or Japan, out-perform their peers elsewhere. The underlying reasons for this do not seem surprising, as innovative cluster firms can get support from national research institutions and policies on talent and funding. However, in the other sectors the role of national factors appears diminished, presumably due to ongoing globalization (Locke and Wellhausen 2014; Binz and Truffer 2017). In this sense sustainable energy technology can be viewed as part of specific national socio-technological transitions, dependent on national policies, while health technology is part of a "global" transition in which national policies play a lesser role. Yet it is important to note that in this study the national dimension is operationalized as the quality of the national innovation system, rather than policies supportive of the sustainability technology sectors, or other relevant national factors. It would therefore be premature to conclude that sustainable energy technology is directly influenced by specific national policies.

Cluster knowledge network characteristics show more similarities between the sustainability technology sectors. Both sectors lack an association with knowledge inflow (hypothesis 7) or network density (hypothesis 10) while both have a positive association with network reach (hypothesis 9):

greater network reach can provide clusters with access to new ideas and technologies (Bathelt, Malmberg, and Maskell 2004). In the reference sector, both network reach and network density show a negative association with cluster innovation performance, which suggests that a degree of knowledge network saturation was reached, beyond which additional network linkages do not raise innovation performance (Boschma 2005; Abbasi and Altmann 2011). The positive significance of knowledge outflow essentially indicates cluster success, because multinational corporations usually establish remote research labs in already-thriving clusters (Awate, Larsen, and Mudambi 2015; Østergaard and Park 2015). A significant association is not observed in sustainable energy technology clusters, although the existence of remote labs is not uncommon in the sector (Awate, Larsen, and Mudambi 2012, 2015). The association between knowledge outflow and innovation performance appears to be negative and falls just below the statistical significance threshold in the sustainable energy sector. A negative result suggests that reverse knowledge flow is taking place due to the presence of remote labs in the cluster. "Reverse" knowledge flow occurs because remote labs are often less connected to the local cluster and more connected to multinational corporations, removing or diverting local knowledge spillovers and knowledge flows away from the local cluster (Dunning 2000; Frost 2001; Frost and Zhou 2005; Ambos, Ambos, and Schlegelmilch 2006).

Table 7.4: Evaluation of cluster innovation performance hypotheses and sectors in which they are rejected.

Hypotheses	**Evaluation**
Hypothesis 3: Agglomeration has a positive association with cluster innovation performance.	Not rejected in all sectors (cluster size, local agglomeration); Rejected in health technology and reference sector (adjacency, regional agglomeration)
Hypothesis 4: Regional specialization has a positive association with cluster innovation performance.	Not Rejected (all sectors)
Hypothesis 5: Corporate research activity has a positive association with cluster innovation performance.	Rejected in sustainable energy
Hypothesis 6: The quality of the national innovation system has a positive influence on cluster innovation performance.	Rejected in health technology and reference sector
Hypothesis 7: Knowledge inflow has a positive association with cluster innovation performance.	Rejected in health technology and sustainable energy
Hypothesis 8: Knowledge outflow has a positive association with cluster innovation performance.	Rejected in sustainable energy
Hypothesis 9: The reach of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Rejected in health technology and reference sector (engineering-based)
Hypothesis 10: The density of the inter-cluster collaboration network has a positive association with cluster innovation performance.	Rejected (all sectors)

Hypotheses	Evaluation
Hypothesis 11: Past cluster innovation performance has a positive influence on current cluster innovation performance.	Not Rejected (all sectors)

Although sectoral differences have already been explored, they are explicitly addressed in hypotheses 2 and 12 (see table 7.5). Hypothesis 2 is partially rejected by the results: although the health technology sector does appear to have a denser knowledge network, it has a lower clustering rate (see section 7.2). The low clustering rate seems specific to the medical devices sector, in which only 24% of patents are found in clusters. Hypothesis 12 is not rejected because of the higher model predictive power of the health technology path dependence model (see table 7.3), which fits with its characterization as a sector in mature development phase.

Table 7.5: Evaluation of sectoral difference hypotheses.

Hypotheses	Evaluation
Hypothesis 2: The health technology sector has a denser knowledge network and a higher rate of agglomeration than the sustainable energy technology sector.	Partially rejected, no higher rates of agglomeration
Hypothesis 12: The health technology sector has stronger path dependence compared to the sustainable energy technology sector.	Not Rejected

7.5 Policy Relevance

The policy relevance of the research has so far remained largely unaddressed in this thesis. However, a basis for discussing policy relevance is now provided by the comparative analysis of sustainability technology sectors presented in this chapter, as well as the findings from earlier chapters. Although the results on policy relevance presented here are merely exploratory, they provide a direction for future in-depth research.

The suitability of the research results for policy applications are assessed in two parts. First, the cluster delineation strategy used in this study is evaluated. Second, a *preliminary* framework of components required in regional cluster policy is presented (Brenner and Schlump 2011; Uyarra and Ramlogan 2012; Njøs and Jakobsen 2016) and compared to the research findings.

The suitability of the cluster identification process has already been partially addressed earlier in this study, namely from a more technical-methodological perspective. The use of a single source of patent data, the application of a home bias correction factor, and the calibration of the clustering algorithm are described in detail in 4.3 of chapter 4. In this section the cluster identification results are viewed from a policy perspective: how useful are they for policy-making? (subsection 7.5.1).

Second, a simple preliminary policy framework for technology cluster development is presented. This framework focuses on regional policy from an evolutionary perspective, with some insights into national economic-technological policy, and follows the broader theoretical perspective of the study. An evaluation of the research findings based on this simple framework provides insight into the extent that regional cluster policies can be adequately informed by the descriptive and explanatory results of this study, including the cluster innovation performance model (subsection 7.5.2).

7.5.1 Policy Application of Cluster Identification

In this study organic cluster identification is used to identify the “real” boundaries of technology clusters, an alternative for using administrative boundaries, which do not always align with the actual spatial concentration of innovation activity. Organic cluster identification provides greater insight into the spatial distribution of innovation activity in terms of both scale and density compared to using pre-existing administrative boundaries. While some technology clusters encompass a single town or city, many clusters encompass multiple cities, and sometimes a cluster extends across state/provincial or even national boundaries. Such a situation also has policy implications: while cluster policy could involve a single local/regional authority or city (Van Geenhuizen and Nejabat 2021), it could also combine multiple spatial-administrative units at different levels through a collaborative framework involving more than one city, region or even country (Park 2014). Especially if a cluster covers *multiple* spatial-administrative units, there is the challenge of sufficient collaboration and co-ordination to guarantee a good alignment of policy-making and implementation. In this sense, an organic technology cluster identification methodology helps identify which local/regional authorities are most relevant to a cluster and subsequently, which authorities should be included in a collaborative cluster policy-making.

Aside from potentially shaping regional cluster policy-making by providing a new spatial perspective on technology clusters, organic cluster identification strategies can also be used to monitor technology clusters and to provide more detailed insight into the spatial structure of clusters, e.g. the identification of smaller “mini” clusters within a larger “macro” cluster.

The cluster identification methodology presented in chapter 4 can be used to regularly update the spatial distribution of clusters based on new patent data, allowing decision-makers to monitor the growth of their own clusters, and that of other clusters. The patent data used to identify clusters can also be used to monitor other features of the cluster, such as its innovation performance, its global knowledge network, the type of actors conducting R&D in the cluster, etc. Due to the time-lag between R&D and patent application, the picture provided by current patent application data are likely several months or a year old. While not “real time,” this may still make the patent data more recent than official statistics or innovation surveys, and therefore a very useful cluster monitoring tool. The fact that patent data are usually freely accessible means that the monitoring of clusters is relatively inexpensive.

As already discussed in chapter 4, the identification of clusters requires some judgement to be made about what constitutes a cluster. Are a handfull of smaller medical devices clusters located between Mannheim and Stuttgart in Germany all part of a larger “macro” cluster? Is the photovoltaics cluster in Hsinchu in Taiwan a separate cluster, or is it part of the Taipei cluster, located 60 km away? These questions do not have simple answers and they show the spatial complexity of technology clusters. This complexity is also illustrated by the heatmaps of cluster innovation activity displayed in appendix A.3. From a policy perspective the heatmaps of cluster innovation activity can also show which locations contribute most to a cluster. For example, the London cluster often incorporates nearby Cambridge and Oxford, which are notable technology clusters in their own right due to the presence of large research-intensive universities located there. A London cluster is in actual fact a London-Cambridge-Oxford cluster. The ability to "zoom in" on certain sub-areas of a cluster depends on the available patent address data. For the USPTO patent database, patent address data are typically aggregated at the city level, which makes it impossible to identify sub-clusters *within* a city. For example, all patents invented in Seoul, South Korea are identified as being from "Seoul." However, the Korean Intellectual Property Office (KIPO) patent database contains detailed address information at the neighborhood-level (*dong*). KIPO data could thus be used for the methodology presented in chapter 4 to generate a more detailed innovation heatmap of a large Korean city such as Seoul.

7.5.2 Policy Framework for Cluster Development Stages

In this section a cluster policy framework is presented that offers multiple strategies for cluster development depending on the technology cluster's development stage. Two groups of policies are identified, namely policies to enhance innovation performance of existing technology clusters, and policies to create and grow new technology clusters. Njøs and Jakobsen (2016) present a *stylized* summary of policies for enhancing cluster innovation performance which can be differentiated or merged depending on the cluster's development circumstances. The authors identify three main strategies: "monocropping," "hubbing," and "blending." Monocropping involves increasing local/regional specialization, a strategy for path extension of emerging clusters, including "smart specialization" (McCann and Ortega-Argilés 2015; Morgan 2017). Hubbing involves increasing global knowledge networks within the same sector for path extension and renewal. Blending involves encouraging local inter-disciplinary research collaboration for path renewal. In addition to these three core strategies, review studies of cluster policy by Brenner and Schlump (2011) and Uyarra and Ramlogan (2012) also highlight the following additional observation: it is beneficial to involve the private sector in early stages of the cluster life-cycle, by encouraging start-ups and providing a support-network. In addition, there is the assumption that the emergence of new technology clusters cannot be triggered in the mature phase of a sector's life-cycle. Concerning this point, there is also counter-evidence from the technological catch-up strategies of Asian countries (Lee 2016), whereby national-level policies support regional cluster policies aimed at enhancing path creating, path following or technological "stage-skipping" development paths. In this sense the potential of cluster policies can be enhanced through targeted and regionally aligned national policy support. These additional observations are incorporated into the cluster policy framework as "supporting" strategies that complement the three aforementioned "core" strategies.

The preliminary cluster innovation policy framework and its three core and two supporting strategies, together with the broad suitability of the descriptive and model estimation results, are shown in table 7.6. The supporting strategies are seen as often overlapping with one of the chosen core strategies. When interpreting the results, it is important to note that the sustainable energy technology sector is an example of a fast-growing emerging sector, whereas the health technology and reference high technology sectors are in a more stable and mature development stage. The "monocropping" strategy is seen as more relevant in emerging sectors, whereas "blending" is more relevant for sectors in a mature development stage (Njøs and Jakobsen 2016).

Table 7.6: Preliminary framework of cluster innovation strategies and suitability of cluster innovation performance results.

Policy Strategies	Suitability of Research Results
Monocropping (Core Strategy): deepening sectoral agglomeration ('smart specialization')	Supported by results for all sectors: cluster size and regional specialization are positively associated with cluster innovation performance.
Hubbing (Core Strategy): expanding inter-cluster links with other clusters from the same sector	Supported by explanatory analysis for the sustainable energy technology and health technology sectors (network reach), but not in reference high technology sectors. Descriptive analysis shows that inter-cluster knowledge networks grow over time.
Blending (Core Strategy): expanding local inter-sectoral R&D collaboration	Inconclusive from explanatory analysis (regional specialization is positive, suggesting no advantage from being located in major urban areas with a more diverse technological base), but supported by the descriptive analysis, as clusters of newly emerging sectors are often created in major urban areas.
Promoting *private sector* R&D (Supporting Strategy)	Supported by explanatory results for Healthcare Technology and Reference High Technology (not statistically significant for Sustainable Energy Technology) and supported by the descriptive analysis as corporate research accounts for the majority of cluster innovation output.
Developing strong *national policies* (Supporting Strategy)	Based on descriptive analysis, China, South Korea, and Taiwan are clearly growing their global share, including in mature industries, suggesting a national policy dimension

The cluster innovation performance results tend to support "monocropping" (local/regional specialization) and "hubbing" policy strategies (enhancing global knowledge networks within the same sector), but tend to be inconclusive with regard to the "blending" strategy. A blending strategy is a growth path whereby different existing local sectors combine into a new sector, something more likely to happen in a major urban area with a diverse technological base. The innovation results do not show that being located in a major urban area raises cluster innovation performance. Instead, regional specialization, whereby certain sectors play a relatively large role within a particular region or city (i.e. low diversification), appears to be positively associated with cluster innovation performance.

The descriptive analysis does provide support for a "blending" strategy. It can be observed that the clusters of several sustainable energy technology sub-sectors have developed in cities with large established industries, such as automotives. In that sense the development of hydrogen technology and energy storage clusters can be seen as a form of "blending" which is extending the path of the automotive cluster into new technological domains. The descriptive analysis also allows for the monitoring of private sector R&D in clusters, although in the sustainable energy technology sector, which is involved in socio-technological transitions, support from other actors beyond the private sector is also important (Geels et al. 2017). In contrast, bringing the technology to market by corporate or university spin-off firms, cannot easily be measured based on patent data.

The descriptive analysis further shows the rapid growth of clusters in China, Taiwan, and South Korea, including in the more mature health technology sector. The growth of clusters in these specific "late industrializing" countries suggests that strong national policies are also in place (Lee 2016). As cluster growth and cluster innovation performance are among the main concerns of cluster policy makers, the cluster methodology provides useful tools for gaining insights in these areas. In future, the model results could be further enhanced by incorporating the development of important organizations (e.g. promising start-ups) and knowledge network linkages (e.g. to other highly innovative clusters and organizations).

Based on the descriptive and explanatory cluster innovation performance analysis, the most obvious insight is that "monocropping" and "hubbing" appear to be suitable cluster development strategies, although "hubbing" in more mature sectors may involve inward and outward investment by multinational corporations, rather than inter-organizational research collaboration. A "blending" strategy may be more relevant to cluster growth than to cluster innovation performance. Furthermore, local/regional cluster policies may be insufficient if attempting to break into mature sectors. In such cases national policy support is also needed, possibly with additional help from European Union policies. Accordingly, in addition to local cluster policies, national and European Union-policies may also be needed to raise the innovation performance and growth of European technology clusters, especially in sectors where Asian or North American innovation activity is very dominant. At the same time, the European Union may also be able to leverage its strengths in areas like citizen science, as an important resource for innovation (Haklay 2015).

In spite of the previous points, the explanatory power of the innovation performance model is also limited in several ways. This is the reason why concerns remain about other conditions that are at stake, but have remained unobserved in the current study due to use of mainly patent-related indicators and a simplified model. What can be mentioned are cultural conditions like differences in risk-taking culture and open creativity (Nooteboom 2013; Autio et al. 2014), actual financial support schemes at the national level (Grau, Huo, and Neuhoff 2012; Palmer et al. 2018), the kind of policy making processes (consensus seeking, authoritative) (Casper 2013; Langhelle, Meadowcroft, and Rosenbloom 2019), and the facilities provided in cities to enhance experimentation and the adoption of new technology (Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Nejabat 2021). In addition, conditions beyond policy control need to be mentioned, like fluctuation of the economy (crisis) and occurrence of natural disasters (climate and health-related), that may work as a trigger in path renewal.

7.6 Conclusion

The sectoral comparison presented in this chapter reveals noteworthy differences in cluster characteristics and their influence on innovation performance, which may also have some policy implications. Some of these differences can be attributed to the development phase and knowledge base of the sectors, while the influence of socio-technological transitions on cluster characteristics appears to be more complex, as each sustainability technology sector appears to be involved in a different type of socio-technological transition. In addition, there is also a link with new regional policy (smart specialization) emphasizing specific regional (natural) assets.

The rapid growth of the sustainable energy technology sector is reflected in its cluster characteristics, including the creation of new clusters, rising agglomeration and growing knowledge networks.

In terms of innovation performance, its clusters lack the diseconomies of scale and network saturation effects found in other sectors, and show lower path dependence. The knowledge base of the health technology sector is evident from its lower corporate research share and dense inter-cluster knowledge network, as compared to other sectors. Network reach is positively associated with innovation performance in both sustainability technology sectors.

Viewing the sustainability technology sectors from the perspective of socio-technological transitions raises complex questions about regional agglomeration (adjacency), corporate research, multinational corporations, and the national innovation system. The negative association with adjacency is absent in the sustainable energy technology sector, raising questions as to why this is the case. Corporate research and the presence of multinational corporations are also not significant in sustainable energy technology clusters, suggesting their diminished role, as compared to other innovation actors, such as the public sector. Evidence for a relatively large role of public and non-profit actors in the sustainable energy technology sector can also be taken from the significance of the national innovation system. Yet there are no hypotheses that explore the relationship between policy (whether local or national) and cluster innovation performance. It is also noteworthy that in all of these aspects, the health technology sector differs and appears to be more similar to the reference high technology sectors, which are not involved in socio-technological transitions.

Sectoral differences are also noted when comparing cluster development strategies to the empirical results. Although “monocropping” (regional specialization) and “hubbing” (global networking) strategies appear to be supported by the results, “hubbing” in more mature sectors appears to involve inward and outward investment by multinational corporations, rather than inter-organizational research collaboration. The role of the private sector also appears to be different in relation to cluster innovation performance: in newly emerging sustainable energy technology sectors it appears related to cluster growth, but not to innovation performance.

In the next chapter (chapter 8) a broad summary and discussion of the empirical results from the past three chapters is presented, including their theoretical and policy implications. Chapter 9 provides further reflection on the results, theory, and research methodology.

Chapter 8

Summary and Discussion

8.1 Introduction

The sustainability technology sectors play a critical role in addressing the large global problems of ageing populations and climate change, specifically the rising demand for medical care and the need to reduce the cost of healthcare (European Commission 2018; World Health Organization 2019), as well as the need to reduce the emission of greenhouse gasses (Intergovernmental Panel on Climate Change 2018; European Commission 2019). While these problems cannot be solved by technological solutions alone, technology plays an important part in addressing them (World Health Organization 2004; International Energy Agency 2016; REN21 2017). Addressing the challenges of innovation, climate change, public health and the need for sustainable industrialization and economic growth are also key parts of the United Nations' Sustainable Development Goals (United Nations 2017).

Viewed spatially, technological innovation tends to follow a pattern of being globally distributed but spatially concentrated in technology clusters, which are connected through a global network of knowledge relationships (Malecki 2014; Ó hUallacháin and Lee 2014; Crescenzi et al. 2019). Cluster agglomeration and knowledge networks are among the factors seen as being closely associated with cluster innovation performance (Feldman and Kogler 2010). However there is a knowledge gap concerning the specifics of these patterns and associations for the sustainability technology sectors. This knowledge gap is summarized by the main research question of this dissertation: *What are the dynamic spatial distribution and innovation performance patterns of sustainability technology clusters and how are they influenced by cluster characteristics, such as agglomeration and knowledge networks, and sectoral differences?*

The global spatial distribution of sustainability technology clusters is discussed in section 8.2 (research question 1), and the agglomeration characteristics and inter-cluster knowledge networks are addressed in section 8.3 (research questions 2 and 7). In section 8.4 different aspects of the relationship between cluster innovation performance and cluster agglomeration, the national innovation system, knowledge networks and path dependence in the sustainability technology sectors are explored (research questions 3-6 and 8). Section 8.5 offers a summary and discussion of the research contributions from a methodological, empirical, theoretical and policy standpoint. A brief conclusion completes the chapter (section 8.6).

8.2 Spatial Distribution

This section provides a discussion of the theory, research questions, and empirical results related to the spatial distribution and dynamics of health technology and sustainable energy technology clusters. The location of sustainability technology clusters, including their creation, growth, or decline, are matters of great importance from the perspective of regional and national innovation performance. Because innovation is an important driver of economic development, and in the case of the sustainability technology sectors also of socio-economic changes and socio-technological transitions (Geels et al. 2011; Geels 2012), the location of technology clusters is of major concern to policy makers at local, regional, national and international levels (Dicken 2007; European Commission 2010, 2013).

Concisely defined, innovation is the ability to generate new knowledge and apply it in an economically useful way (Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005). As is the case with many other kinds of economic activity such as finance, corporate headquarter governance, air transportation and telecommunication, innovation activity is concentrated in a relatively small number of locations distributed around the globe, which form well-connected global networks (Malecki 2014; Belderbos, Du, and Goerzen 2017). These "world" or "global" cities tend to be hubs within the global networks of professional services, finance, telecommunications, and air transportation (Taylor 2004; Ichikawa, Yamato, and Dustan 2017), and they often contain large concentrations of innovation activity (Bergquist, Fink, and Raffo 2017; Florida, Adler, and Mellander 2017). However, not all large metropolitan areas have reached such an advanced state of development.

It is important to note that large clusters are not necessarily located in "world" or "global" cities; the geographic locations of clusters varies depending on the sector. Life sciences clusters are often found in smaller cities and are often anchored around universities (Ó hUallacháin and Lee 2014). Some sustainable energy technology clusters are found in more remote locations in order to take advantage of local natural assets (Van Geenhuizen and Holbrook 2018). The location of clusters is also dynamic: in young and fast-growing sectors there is significant cluster creation (Ter Wal and Boschma 2011), whereas in more mature sectors growth tends to take place within existing clusters (Frenken, Cefis, and Stam 2015). Especially in sectors involved in socio-technological transformations, R&D clusters are likely to grow and benefit in places that, aside from R&D facilities, also offer policy and other support, creating space for experimentation and opportunities for new technologies to find early adopters, like niches and living labs (Smith and Raven 2012; Steen and Hansen 2018; Van Geenhuizen and Ye 2018).

The global spatial distribution of sustainability technology clusters, and the changes therein, have not been previously explored in the scientific literature, thus leading to **Research Sub-question 1:** What is the global spatial distribution of sustainability technology clusters and how has it changed in recent years? **Supporting sub-question 1.1:** How can sustainability technology clusters be identified on a global scale? **Supporting sub-question 1.2:** Where are the largest sustainability technology clusters located during different periods? **Supporting sub-question 1.3:** Where are growing and shrinking sustainability technology clusters located? The answers to these questions are discussed below, addressing the global spatial distribution and spatial dynamics of sustainability technology clusters.

With regard to identification and spatial delineation of clusters, sustainability technology clusters are identified from patent data, using a "heat map" organic cluster identification methodology.

This exercise provides a global overview of technology clusters from the various sustainability technology sectors and sub-sectors for different time periods, allowing sectoral differences and dynamics to be observed (see also chapter 4).

In terms of their global spatial distribution, the 10 largest health technology clusters are all found in large "global" cities such as San Francisco, Tokyo, New York, Los Angeles, Seoul, and Taipei (Taylor 2004; Ichikawa, Yamato, and Dustan 2017). This is also the case for the reference high technology clusters. This pattern aligns with assumptions that in large cities, R&D organizations of companies and universities can lower transportation and transmission costs, provide proximity to markets, increase the chance of two agents meeting (eventually, serendipity) and encourage the exchange of creative ideas (especially for interdisciplinary projects). Large cities also create economies of scale, attracting specialized business services and talent (Morgan 2004; Capello 2009; Florida, Adler, and Mellander 2017). Further agglomeration-like advantages are found in cities through "relational proximity," providing the opportunity to learn through collaboration with other regions or clusters located further away (Camagni and Capello 2002; Boschma 2005; Cohendet and Amin 2006; Morrison, Rabellotti, and Zirulia 2013).

The spatial pattern of sustainable energy technology clusters is very different from the health technology clusters: around half of the 10 largest sustainable energy technology clusters are found in cities such as Daejeon, Detroit, Nagoya, and Stuttgart, which are in the lower tiers, or not included, in global city lists such as the *World City Network* (Taylor 2004; Taylor and Derudder 2015) or the *Global Power City Index* (Ichikawa, Yamato, and Dustan 2017). When observing the sustainable energy technology sub-sectors included in this study, a number of large clusters are found in small cities. This pattern is especially strong in the biofuels and wind turbines sectors where the top-10 clusters are found in cities like Aarhus (Denmark), Aurora (Colorado, United States), and Pamplona (Spain). The presence of sustainable energy technology clusters in specific small cities is typically linked to policy decisions, or is part of an evolutionary development. Daejeon in South Korea is targeted for sustainable energy research by the national government (Wu 2014; Jeong 2017) whereas Detroit, Nagoya, and Stuttgart are home to large automotive industries (General Motors, Toyota, Mercedes-Benz, etc.), which have expanded their electric vehicle R&D (International Energy Agency (IEA) 2019a). These empirical results confirm earlier research which suggests that sustainable energy technology clusters tend to form in locations with specific location-dependent resources (such as natural assets), institutions, or policy interventions (Coenen, Benneworth, and Truffer 2012; Van Geenhuizen and Holbrook 2018; Steen and Hansen 2018). The pattern in particular aligns with specific prior policies on "smart specialization" and avoiding lock-in (McCann and Ortega-Argilés 2015; Morgan 2017).

With regard to the global distribution of clusters and innovation activity, health technology is more concentrated in North America whereas sustainable energy innovation is more concentrated in Asia. Europe is lagging in both sectors, although it plays a prominent role in some sub-sectors such as wind turbines. Electric vehicles and related sub-sectors (electricity storage and fuel cells) are mainly concentrated in Asia (56%, Japan and South Korea in particular), while biofuels R&D is mainly found in North America (62%).

The sustainable energy technology sector shows particularly strong spatial dynamics. The sector grew rapidly during the period, with a 192% increase in patent output and a 149% increase in the number of clusters between 2000-2004 and 2008-2011. In contrast, the number of clusters and patents for the health technology sector was generally stable (+/- 5%) over the same period. The sustainable energy technology sector increased by 100 clusters, raising its cluster population to

176 clusters. In addition, most new clusters were created in North America (+44 clusters, +147% increase). In relative terms, most clusters were created in Europe (+383% based on 23 clusters). Asia experienced the smallest cluster increase in absolute and relative terms (+31 clusters, +100% increase), but maintained the largest share of sustainable energy patent output (42-43% of world output).

Amid these spatial dynamics, there is no clear evidence of a shift in sustainable energy innovation towards Asia (Dicken 2007). Instead, it appears that Asian countries, with Japan and South Korea as the main contributors, were already positioned ahead of Europe and North America in sustainable energy technology at start of the study's observation period in 2000. The strong position of South Korea and Japan has been built up since the oil crisis in the late 1970s, when both countries, which are major hydrocarbon importers, implemented policies promoting the adoption of renewable energy. In addition, specific parts of sustainable energy research are often connected to other advanced and export-oriented manufacturing industries, such as semiconductors (photovoltaics), automobiles (electric vehicles), and offshore structures and shipbuilding (wind turbines) (Haslam, Jupesta, and Parayil 2012; Chen, Kim, and Yamaguchi 2014). In Japan and South Korea, sustainable energy industries have developed through a combination of public and private investment, nd with a strong focus on export demand. Chen, Kim, and Yamaguchi (2014) note that, after an initial energy-efficiency drive to respond to the 1970's oil crisis, domestic sustainable energy targets have often remained quite low compared to other advanced economies as a way to maintain domestic economic competitiveness. This may be a noteworthy difference in economic policy compared to North America and Europe, where policies to promote sustainable energy technology innovation are focused on local adoption and use of these technologies (Grau, Huo, and Neuhoff 2012; Nielsen 2017), instead of export promotion. Rather than showing an inter-continental shift, the pattern of global shifts in sustainable energy technology is multi-directional, with some countries growing their share of global sustainable energy research (including China, Denmark, France, South Korea, Taiwan and the United States) and others declining in relative terms (including Canada, Germany, Japan and the United Kingdom). The leading position of countries like Japan, as well as South Korea, Taiwan and soon China in sustainable energy technology R&D, fits with a broader trend of Asian countries leading technological development in key sectors (Joo, Oh, and Lee 2016; Ahn 2017; Miao et al. 2018).

The health technology sector is notably different in terms of its spatial dynamics, which is attributable to its mature and path dependent development phase. This will likely preserve or strengthen existing cluster hierarchies (including rankings) and knowledge networks (Martin and Simmie 2008; Crescenzi and Rodríguez-Pose 2011). Nevertheless, there are countries and cities that are increasing their relative share of global healthcare patent output. Notable examples include South Korea and Taiwan and the cities of Seoul, Daejeon and Beijing. These countries have significantly increased public health technology research expenditure in recent decades, and have aggressively supported the development of local firms (Lee, Tee, and Kim 2009; Chakma et al. 2014; Lee and Yoon 2018). Cities like Seoul, Daejeon and Beijing are also home to highly-ranked research universities (Seoul National University, Korea Advanced Institute of Science & Technology, Beijing University, Tsinghua University, etc.) which can support these developments (Waltman et al. 2012). While investment, policy support and high quality university research are also available in other cities, they appear to be developing rapidly in specific Asian countries and cities.

8.3 Agglomeration and Inter-Cluster Knowledge Networks

This section contains a brief description of the theory, research questions, and empirical results related to the agglomeration characteristics and global inter-cluster knowledge networks of the sustainability technology clusters, including an analysis of the main sectoral differences. Agglomeration and knowledge networks are both seen as important features of technology clusters. Agglomeration (spatial proximity) facilitates social interactions, inter-organizational relationships, and can provide multifaceted cost advantages due to economies of scale (Porter 2000; Malmberg and Maskell 2002; Gertler and Levitte 2005; Nooteboom 2006). Interactions within a technology cluster include research collaborations between different actors (Porter 1998; Kerr and Robert-Nicoud, n.d.), learning, and stimulating competitive drive between firms and researchers operating in the same cluster (Porter 2000; Malmberg and Maskell 2002).

Clusters are often highly connected to global knowledge networks (relational proximity) and appear to benefit in ways that are similar to how agglomeration facilitates collaboration and knowledge spillovers within clusters (Boschma 2005). Knowledge networks typically consist of a collaborative relationship involving the transfer and co-creation of knowledge, which can span a range of different institutional contexts, goals and power relations (Bukvova 2010; Fitjar and Rodríguez-Pose 2014; Comunian 2017; Capone, Lazzeretti, and Innocenti 2019). International and inter-cluster research collaboration is especially prevalent in knowledge-intensive sectors such as biotechnology and pharmaceuticals (Ó hUallacháin and Lee 2014; Alkemade et al. 2015; Persoon, Bekkers, and Alkemade 2020).

While the aforementioned theoretical perspectives provide a basic framework for understanding cluster agglomeration and knowledge network patterns, little is known about the specific circumstances of the sustainability technology sectors. This knowledge gap leads to **Research Sub-question 2:** What are the agglomeration and knowledge network characteristics of sustainability technology clusters and how have they changed in recent years? **Supporting sub-question 2.1:** What are the clustering rates and average cluster size? **Supporting sub-question 2.2:** What is the density and reach of knowledge network links?

A further knowledge gap exists concerning the sectoral variations in agglomeration and knowledge networks, which depend on a sector's development phase, knowledge base, and market structure (Ter Wal and Boschma 2011; Binz and Truffer 2017). The agglomeration and density of knowledge networks tends to increase over time as sectors mature, and growth takes place mostly in existing clusters (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). In sectors with a scientific knowledge base, knowledge tends to be more codified, facilitating collaboration over long distances (Carlsson 2013; Persoon, Bekkers, and Alkemade 2020). Sectors with an engineering and design knowledge base innovate through close interactions with customers and suppliers, and through "learning by doing," enabling the accumulation of experience and specialized skills (Jeannerat and Kebir 2016). Market structure and regulation of sectors are also points of differentiation. Some sectors experience relatively free competition, while in a sector such as healthcare there are regulators, insurers, hospitals, and physicians who play an important role in mediating between producers and end-users (Binz and Truffer 2017; OECD 2017; Lopes et al. 2019). Addressing these sectoral differences is **Research Sub-question 7:** What are the differences between the health technology and sustainable energy technology sectors against the background of other high technology sectors, in terms of their spatial distribution, agglomeration and knowledge network characteristics? **Supporting sub-question 7.1:** To what extent can sectoral differences be attributed to the sectoral knowledge base? **Supporting sub-question 7.2:** To what extent can sectoral differences be attributed to the sectoral development phase? **Supporting sub-question 7.3:** To what extent can sectoral differences be attributed to socio-technological transitions? The answers to these research questions are discussed below, with a description of the agglomeration and the inter-cluster knowledge networks of the sustainability technology sectors, and an analysis of the differences between them. The issue of sectoral aggregation is also addressed.

With regard to agglomeration, both sustainability technology sectors have a similar share of clustered patents (42-47%) and a similar Gini coefficient of cluster size (0.67-0.69), although the health technology sector has a larger number of patents per cluster (133.2-149.8) as compared to the sustainable energy technology sector (44.2-67.4). The sustainable energy technology sector is undergoing rapid growth, coinciding with an increase in agglomeration, seen both in the share of clustered patents (+31%) and in the Gini coefficient of cluster size (+5%). Increasing agglomeration is typical of emerging sectors transitioning towards a mature development phase (Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015). Qualitative agglomeration indicators such as corporate research, show a divergence between the two sustainability technology sectors. Corporate research accounts for 85.8% of the sustainable energy technology sector, compared to 73.4% for the health technology sector.

Regarding knowledge networks, the number of co-invention links per inventor is 0.32 for sustainable energy, and 0.41 for healthcare. Both differences are statistically significant. These differences fit with the health technology sector's characterization as having a scientific knowledge base. Science-based sectors typically have higher participation by university and government actors and relatively frequent long-distance research collaboration (Owen-Smith et al. 2002; Alkemade et al. 2015; Binz and Truffer 2017).

In the context of comparing results between the two sustainability technology sectors, it is important to mention several basic aggregation issues, as both sectors are aggregates of different sub-sectors. First, some sub-sectors within the same aggregate sector have a scientific knowledge base, while others are seen as having a design and engineering knowledge base. Second, there are also large differences in terms of the clustering rates of sub-sectors: in the health technology sector the clustering rate is 72% for medical life sciences but only 24% for medical devices. In the sustainable energy technology sector, the clustering rate is between 72% for electric vehicles and only 27% for electricity storage (fuel cells; batteries) and 33% for wind turbines. Notable differences can also be found in other cluster characteristics. The high level of sub-sector heterogeneity suggests that caution is needed when generalizing aggregate sector results to individual sub-sectors.

8.4 Innovation Performance of Technology Clusters

The innovation literature identifies a number of conditions that are seen to influence, or are associated with, cluster innovation performance. The current study has focused on the following conditions: agglomeration, the national innovation system, knowledge networks, and path dependence, which are seen in the literature as the most important factors influencing cluster innovation performance. Understanding which conditions affect cluster innovation performance, and to what extent, is highly relevant for decision makers in the private and public sector who seek to raise the innovation performance of technology clusters. Yet, debate exists about the direction (positive or negative) and relative importance of these conditions. Agglomeration can be both positive and negative, with negative influence arising due to diseconomies of scale in very large cities, eventually causing competition for scarce urban assets, and emergence of congestion and higher labor and living costs (Martin and Sunley 2003). There is also discussion about the extent to which the national innovation system influences cluster innovation performance, as there may be little variation between countries that host prominently innovative clusters (Dicken 2007; Binz and Truffer 2017). Additionally, global knowledge networks can enhance a cluster's access to knowledge, but in certain situations they can also lead to knowledge outflow (Frost and Zhou 2005; Ó hUallacháin and Lee 2014). Also, while path dependence can lead technology clusters to persistent high innovation performance over long periods of time, it can also trap them in old technological development paths, preventing the forging of new paths (Martin and Simmie 2008; Crescenzi and Rodríguez-Pose 2011; Østergaard and Park 2015; Trippl et al. 2015).

This section consists of four subsections, which address the research questions and empirical results related to agglomeration (research question 3, subsection 8.4.1), the national innovation system (research question 4, subsection 8.4.2), knowledge networks (research question 5, subsection 8.4.3) and path dependence (research question 6, subsection 8.4.4). In addition the sectoral differences in cluster innovation performance are also discussed: **Research Sub-question 8:** What are the differences between the health technology, sustainable energy, and other high technology sectors in terms of cluster characteristics (agglomeration, knowledge network, national innovation system, and path dependence) and cluster innovation performance? **Supporting sub-question 8.1:** To what extent can differences in association be attributed to the sectoral knowledge base? **Supporting sub-question 8.2:** To what extent can differences in association be attributed to the sectoral development phase? **Supporting sub-question 8.3:** To what extent can sectoral differences be attributed to socio-technological transitions? Sectoral differences are addressed in each of the following subsections (8.4.1 to 8.4.4).

Overall, the empirical results show a positive association between cluster innovation performance and certain kinds of agglomeration and knowledge network relations, specifically: cluster size, regional specialization, corporate research, knowledge out-flows and network reach. However, a negative association is observed for other factors, including adjacency. These findings complement relatively recent research, which shows that agglomeration and knowledge networks can also act as barriers to innovation performance, or only contribute under specific circumstances, or are beneficial only for some firms (Suire and Vicente 2009; Potter and Watts 2010; Lee 2018; Capone, Lazzeretti, and Innocenti 2019; Tomás-Miquel, Molina-Morales, and Expósito-Langa 2019). The following sub-sections provide a discussion of the empirical findings related to the innovation performance of technology clusters.

8.4.1 Agglomeration Conditions

Agglomeration is a multidimensional concept, acting at different spatial scales, and consisting of qualitative and quantitative components. From this broad perspective, the following research questions are formulated: **Research Sub-question 3:** To what extent can the agglomeration characteristics of a technology cluster be associated with its innovation performance? **Supporting sub-question 3.1:** To what extent can agglomeration economies be associated with cluster innovation performance? **Supporting sub-question 3.2:** To what extent can regional specialization be associated with cluster innovation performance? **Supporting sub-question 3.3:** To what extent can corporate research (as a proxy for absorptive capacity) be associated with cluster innovation performance?

From a first glance at the empirical results of this study, the association between agglomeration and cluster innovation performance appears relatively simple: cluster size and corporate research are both positively associated with cluster innovation performance, although in the sustainable energy technology sector the association with corporate research is not statistically significant. The results follow existing theory about local agglomeration economies, including a larger local market of specialized suppliers, customers, collaborators and skilled labor, greater opportunities for knowledge spillovers and performance-enhancing competition (Porter 1998; Morgan 2004; Capello 2009; Feldman and Kogler 2010; Fazio and Lavecchia 2013; Giuliano, Kang, and Yuan 2019; Kemeny and Storper 2020). The importance of corporate research is linked to the cluster's absorptive capacity and strategy formulation: the local presence of firms with adequate research and innovation capabilities is essential for the cluster to benefit from local knowledge spillovers from universities and other firms (Fu 2008; Qiu, Liu, and Gao 2017). A large presence of only university and government research, and a lack of corporate research, signals a lack of local absorptive capacity and is seen as a barrier to cluster innovation performance (Ó hUallacháin and Leslie 2007; Casper 2013).

The empirical results become more complex when noting that negative agglomeration economies exist if a cluster is located within relatively close proximity to other large clusters of the same sector (< 200 km, adjacency effect). This suggests that collaboration and competition patterns differ depending on the distance at which they occur. In practice, clusters are usually found within close proximity if they are part of the same conurbation. For instance, the Utsunomiya, Mito and Chiba clusters are all located within 200 km of Tokyo, and can hence be considered to be part of "Greater Tokyo." While being part of Greater Tokyo might provide some agglomeration benefits, by increasing access to specialized services, suppliers, customers, labor, etc., the costs of increased competition appear to outweigh these benefits, causing a negative agglomeration effect to be observed in this study (Richardson 1989, 1995; Zheng 2001; Martin and Sunley 2003).

With regard to the aforementioned observations, it must be noted that neither adjacency nor corporate research appear to have a statistically significant association with innovation performance of sustainable energy technology clusters. The association is only statistically significant in the health technology sector and in the reference high technology sectors. Viewed from the perspective of the sector's development phase, it is possible that negative agglomeration effects have not been reached *yet* due to the rapid growth of sustainable energy clusters and still low levels of agglomeration (Frenken, Cefis, and Stam 2015). Viewed from the perspective of socio-technological transitions, it is possible that competition within the sector and the role of corporate research differ because of a relatively stronger involvement of government, civil society, and other stakeholders in influencing sustainable energy innovation (Geels et al. 2017).

8.4.2 National Innovation System

The role of the national innovation systems appears to be in decline, as individual technology clusters and global supply chains are seen to play a more powerful role than national policies and institutions (Porter 2000; Gertler and Wolfe 2006; Binz and Truffer 2017). Yet, national governments continue to play an important role in developing national innovation capacity through investments in education, encouraging entrepreneurship, and policies that support R&D and innovation (Dicken 2007; Palmer et al. 2018). In Europe, this happens among other areas in the framework of large European Union research programs. However, strong participation by many member countries in such programs may also contribute to similarity of national innovation systems. Accordingly, the influence of the national innovation system on sustainability technology clusters is not well understood, leading to **Research Sub-question 4:** To what extent does the quality of the national innovation system influence cluster innovation performance?

Based on this study, the national innovation system is only statistically significant in the sustainable energy technology sector. This result suggests that national institutions or policies influence sustainable energy innovation performance to a greater extent than in other sectors.

A strong national innovation system may be more capable of stimulating the early market adoption of energy innovations, which often face resistance from users due to higher costs, less user convenience and changes to existing distribution and business models. Overcoming such obstacles may require national-level policies, and there is evidence that specific national policy interventions have encouraged the development of a particular sustainable energy technologies (Boeckle et al. 2010; Grau, Huo, and Neuhoff 2012). Because of the need to change socio-technological systems and business models, sustainable energy innovation has a diverse landscape of actors including civil society, media, government (at various levels), regulatory bodies, financial investors, political parties and advisory bodies, in addition to consumers and firms, which may or may not have vested interests (Geels et al. 2017; Langhelle, Meadowcroft, and Rosenbloom 2019). This creates a different innovation context as compared to other high technology sectors.

8.4.3 Inter-Cluster Knowledge Networks

Some of the advantages and disadvantages of agglomeration (spatial proximity) noted earlier show parallels to phenomena observed in knowledge networks external to the cluster. This "relational proximity" can be seen as a non-spatial agglomeration effect, whereby innovation actors are connected to partners outside of the cluster, in relationships that involve the transfer and co-creation of knowledge (Boschma 2005; Asheim and Gertler 2005; Ponds, Oort, and Frenken 2009). There is, however, some ambiguity concerning the influence of relational proximity on cluster innovation performance. While generally viewed as positive, in some instances international research collaboration has been found to weaken local research activity and interaction (Kwon et al. 2012; Van Geenhuizen and Nijkamp 2012; Ye, Yu, and Leydesdorff 2013). Furthermore, network relationships that involve knowledge being acquired by parties located outside a cluster can also have a negative effect. Such a situation can develop when multinational organizations set up or acquire remote research labs in a cluster causing a "reverse" knowledge outflow (Ambos, Ambos, and Schlegelmilch 2006; Frost and Zhou 2005). However, multinationals have a tendency to invest in already-thriving clusters (De Propris and Driffield 2005; Liu and Buck 2007) and their presence can also signal a cluster's high innovation performance. These considerations lead to **Research Sub-question 5:** To what extent can knowledge networks be associated with enhanced cluster innovation performance and what is the nature (positive or negative) of this association? **Supporting sub-question 5.1:** To what extent can inter-cluster research collaboration networks be associated with cluster innovation performance? **Supporting sub-question 5.2:** To what extent can inbound and outbound knowledge flows be associated with cluster innovation performance?

The empirical results show a positive association between a cluster's global knowledge network position and its innovation performance. Access to a large number of different clusters (network reach) is positively associated with cluster innovation performance in the sustainability technology sectors. This supports the view that access to diverse knowledge can positively contribute to cluster innovation performance (Bathelt, Malmberg, and Maskell 2004; Gertler and Levitte 2005; Ebersberger and Herstad 2013; Hottenrott and Lopes-Bento 2014). The ratio of network links relative to the size of the cluster does not show a significant association in the sustainability technology sectors.

Inbound and outbound knowledge flows, as facilitated by multinational corporations, do not appear to have a significant association in sustainable energy technology clusters, although there is a negative association for knowledge outflow, which is just below the 90% statistical significance threshold. This result suggests that eventually there may be an issue with “reverse” knowledge flows in sustainable energy technology clusters (Frost and Zhou 2005). However knowledge outflow is positively associated with cluster innovation performance in the health technology clusters. It is plausible that young and relatively small clusters, which may be more frequently found in an emerging sector like sustainable energy technology, are more sensitive to “reverse” knowledge flows. Promising innovations originally developed in a small cluster may be transferred to a large cluster by relocating some key researchers, something that can have a big impact on the small cluster where the innovation originated.

8.4.4 Path Dependence

Path dependence is often seen as positively associated with cluster innovation performance because knowledge, relationships, experience, skills, trust, reputation, and other conditions which can enhance cluster innovation performance, accumulate over time (Vergne and Durand 2011; Trippl et al. 2015; Crescenzi and Jaax 2017). Conceptually, path dependence cuts across the aforementioned agglomeration and knowledge network concepts because clusters and knowledge networks also develop over time and are therefore part of a cluster’s development path (Ter Wal and Boschma 2011; Crescenzi and Jaax 2017). However, path dependence can also prevent the development or adoption of new technologies because of a reluctance or inability to abandon existing skills, expertise and knowledge (Vaan, Frenken, and Boschma 2019). Emerging sectors, such as sustainable energy technology, are seen as having weak path dependence because they are in a path creating development phase (Martin and Simmie 2008; Essletzbichler 2012). This ambiguity leads to: **Research Sub-question 6:** To what extent can the path dependence characteristics of a technology cluster be associated with its innovation performance?

In both sustainability technology sectors in this study, path dependence has a significant and positive influence on cluster innovation performance. In the health technology sector, path dependence has a stronger association with cluster innovation performance than in the sustainable energy technology sector. This is an observation that fits with the characterization of sustainable energy technology as an emerging sector that is in a path creating development phase.

8.5 Research Contributions

The study makes contributions that apply to four different areas: the cluster identification process and the design and testing of the innovation performance model (methodological contribution, subsection 8.5.1), novel empirical results (empirical contribution, subsection 8.5.2), new theoretical insights and the identification of new knowledge gaps (theoretical contribution 8.5.3), and new insights that may support cluster innovation policy-making (policy contributions, subsection

8.5.4). The theoretical contribution includes the observation of opposing agglomeration effects at different spatial scales (local and regional) and an understanding of the influence of social-technological transitions on cluster spatial dynamics and cluster innovation performance. The policy contributions lie in identifying and monitoring clusters, and a better understanding of barriers and supporting factors for cluster innovation performance, which can be addressed in regional, national, and European-level cluster policies.

8.5.1 Methodology: Cluster Identification Methodology and Innovation Performance Model

The methodological contribution of this study lies in both the cluster identification process and the operationalization of the cluster innovation performance model using patents as the basis of measurement. The identification of clusters based on the real locations of innovation activity from patents or other scientometric data has previously been undertaken by a few researchers, but mainly as a demonstration of the potential of the methodology. Catini et al. (2015) and Alcácer and Zhao (2016) used a similar methodology to identify sectoral clusters, while Bergquist, Fink, and Raffo (2017) produced an international ranking of technology clusters.[1] Alcácer and Zhao (2016) demonstrated in detail the advantage of using an "organic" cluster identification methodology instead of using preset administrative boundaries. Especially in an international context the use of sub-national administrative boundaries is complicated because of the large variations in the size of administrative units. The advantage of using an organic cluster identification methodology is that the real spatial scale of the cluster is revealed, which may cover a single city, an urban corridor, or even parts of several bordering countries. These observations provide insight into the true location of clusters, which ideally should be taken into account when conducting cluster research or cluster policy-making and coordination.

The cluster identification methodology developed in this study is improved by the use of a single patent data source, a home bias correction factor, the careful calibration of clustering parameters, and a comparison of the method's performance across multiple sectors. The use of a single patent data source, in this case from the United States Patent and Trademark Office (USPTO), ensures that all patents are evaluated against a uniform standard (Toivanen and Suominen 2015). This is important when making international comparisons, and when using patent data to measure various cluster characteristics. A drawback to using a national patent database is the need for a home bias correction, as the home country, the United States in the case of the USPTO, is over-represented in the database compared to foreign countries (Bacchiocchi and Montobbio 2010). The home bias correction factor used in this study is calculated in a relatively simple and transparent way and is used for certain patent and citation-based cluster indicators.[2] The calibration of cluster

[1] As noted in chapter 4, Bergquist, Fink, and Raffo (2017) estimates that of the 10 largest clusters, 6 are in Japan, China and South Korea which are also the three countries whose patents are considered to be over-represented in the WIPO database (Laurens et al. 2015). The present study places only 3 of the 10 largest clusters in these three countries and also includes Taipei, Taiwan as a top 10 cluster (see table C.12, appendix C.4). Stek (2019) uses a mix of patent data and national research expenditure and places 4 of the 10 largest clusters in Japan, China and South Korea (2007-2011) and also includes Taipei. Taiwan does not appear in the research by Bergquist, Fink, and Raffo (2017).

[2] The influence of the home bias correction can also be tested by introducing a dummy variable for the home country in the model estimations (United States). If this dummy variable lacks statistical significance, the home bias correction can be seen as reasonable (which is the case in this study).

identification parameters delivers a robust methodology that performs well across 19 different high technology sectors, and which can presumably be used for other sectors as well.

The second part of the methodological contribution is the operationalization of the cluster innovation performance model, and the extraction of 10 cluster indicators from cluster patent data, a significant leap compared to earlier organic cluster identification studies (Bergquist, Fink, and Raffo 2017; Stek 2019). Of these 10 indicators, six are novel, in the sense that they have not previously been applied in knowledge production-type functions, or have been operationalized in different ways. The novel indicators are innovation performance, adjacency, regional specialization, corporate research, knowledge inflow, and knowledge outflow.

The cluster innovation performance model itself is relatively simple and straightforward without indirect relations, as adapted from earlier knowledge production functions (Ponds, Oort, and Frenken 2009; Charlot, Crescenzi, and Musolesi 2014; Crescenzi and Jaax 2017). The most significant change is the use of innovation performance (relative citation counts) as the dependent variable, instead of patent counts. The simplified character of the innovation performance model is also motivated by being a first step covering two sectors and many subsectors, thereby preparing the ground for more sophisticated analysis of sustainability-related technology clusters in future research.

Innovation performance is measured based on patent citations per inventor. The reason is that citations represent the value of the innovations that have been patented (Hall, Jaffe, and Trajtenberg 2005), and are therefore considered to be a better measure of innovation performance than patent counts, as most patents are never cited and do not contain important or valuable innovations. The model is used to analyze the innovation performance of a cluster based on its cluster characteristics in a more precise way because the dominant independent variable in knowledge production functions, knowledge inputs, is removed.

More generally, the methodology presented in this study facilitates research about innovation and R&D in ways that were practically impossible in the past due to a lack of sectoral, historical, or global data. At least 10 patent-based indicators are used in this study, providing insight into many different cluster characteristics, including cluster innovation performance. The patenting frequency in a particular sector appears to be the only significant limitation, as very low patenting frequencies would limit the analysis.

8.5.2 Empirical: Spatial Distribution and Cluster Characteristics

The novel methodology used, particularly with respect to cluster identification, ensures that the study produces important new empirical results concerning the changing spatial distribution, knowledge networks and sectoral differences of sustainability technology clusters, an aspect of the sustainability technology sectors that was largely unexplored. The present study identifies sustainability technology clusters, cluster creation and changes in agglomeration and inter-cluster knowledge network patterns, providing a unique global database of sustainability technology clusters at the level of sub-sectors such as medical devices or photovoltaics. The breadth of the results facilitate sectoral and international comparisons.

The results provide a more detailed perspective on "global shifts" of innovation activity between continents, showing different countries and cities experiencing relative growth and decline. This includes some declining clusters in Asia, notably Japan, and many rising clusters in Europe and

North America. Within Asia, clusters in China, South Korea, and Taiwan tend to experience high patent growth. In the United States, some very large city clusters, like New York and San Francisco, have tended to stop growing in favor of smaller large cities such as Denver.

By relating various cluster conditions to cluster innovation performance, the study enables a quantitative analysis of the influence (or strength of association) between these conditions and innovation performance, which is new. The empirical results are also novel in terms of their broad scope. Earlier knowledge production studies at the sub-national level have been limited in their geographic reach to a single country or a group of countries (European Union) and have focused on aggregate innovation activity and not on specific sectors (Ó hUallacháin and Leslie 2007; Ponds, Oort, and Frenken 2009; Charlot, Crescenzi, and Musolesi 2014; Crescenzi and Jaax 2017).

8.5.3 Theory: Cluster Characteristics and Innovation Performance

To frame the theoretical contributions of this study, the sectoral differences and socio-technological transitions of the sustainability technology sectors can be approached from five main theoretical perspectives: (i) broad spatial trends: shifts of economic activity (including innovation) towards Asia, changing locational advantages and an evolutionary view of knowledge network and agglomeration (Kojima 2000; Dicken 2007; Ter Wal and Boschma 2011), (ii) the association between cluster innovation performance and agglomeration, including economies of scale, knowledge diversity, knowledge spillovers and social capital (Nooteboom 2006; Fazio and Lavecchia 2013), (iii) influence of the national innovation system, which includes national institutions, regulation, policies, markets and entrepreneurial culture (Palmer et al. 2018), (iv) knowledge networks that create relational proximity and knowledge pipelines, facilitating global knowledge flows (Bathelt, Malmberg, and Maskell 2004; Boschma 2005) and (v) the path dependence and spatial evolutionary perspectives on innovation performance (Martin and Simmie 2008). A summary of these theoretical perspectives is provided in table 8.1 along with the ways in which the empirical findings differ from or comply with the theoretical perspectives. This is followed by a brief discussion of the model estimation methodology and results, and whether they can be generalized to other sectors not included in the study.

Starting with theoretical perspective 1a (hypothesis 1), the growth of the two sectors is concentrated not just in Asian cities (specifically cities in China, South Korea and Taiwan), but also in cities in North America and to a lesser extent Europe: no European city is among the 10 fastest-growing cities in the health technology sector, while only Berlin is among the fastest growing cities in the sustainable energy sector. North America has seen the largest increase in new sustainable energy technology cluster creation during the study period. Therefore it appears that both local factors and global trends play an important role in cluster creation and growth (Dicken 2007; Van Geenhuizen and Holbrook 2018). Other broad spatial trends in theoretical perspective 1b (hypothesis 2) can be explained from the evolutionary perspective of increasing agglomeration and denser spatial networks over time, a trend that is confirmed in the fast-growing sustainable energy technology sector, whose clustering rate and knowledge network density increase over time (Ter Wal and Boschma 2011). However the mature medical devices sector has a very low clustering rate, suggesting that other factors such as a sector's knowledge base can be a more significant influence (Carlsson 2013). In the case of medical devices in Europe, the sector often developed in smaller cities, taking advantage of existing skills and knowledge in related fields, such as fine mechanics (Klein, Banga, and Martelli 2015).

Theoretical perspectives on agglomeration economies are supported and extended (theoretical perspectives 2a & 2b, hypotheses 3-5): both advantages and disadvantages of agglomeration are identified in the study. Agglomeration advantages appear to act at the local level of the cluster. Agglomeration disadvantages are found at the wider regional level (up to 200 km) from the cluster. These findings shed new light on the concepts of adjacency and neighborhood effects, which are often seen as a positive influence on innovation performance (Giarratani, Hewings, and McCann 2013; Clark and Wójcik 2018). Corporate research is found to be positively associated with cluster innovation performance (Ó hUallacháin and Leslie 2007).

The importance of the national innovation system (theoretical perspective 3, hypothesis 6) has been questioned in the literature (Binz and Truffer 2017). The empirical findings show that the national innovation system is statistically significant in the sustainable energy technology sector, but this is not the case in other sectors. This situation could be due to a lack of strong differences, as most technology clusters are in countries with a high-performing national innovation system.

With regard to knowledge networks (theoretical perspectives 4a & 4b, hypotheses 7-10), knowledge flows mediated by multinational corporations are seen as positively associated with cluster innovation performance (Awate, Larsen, and Mudambi 2015; Østergaard and Park 2015). This view is confirmed in the health technology sector. In terms of the importance of knowledge networks to innovation performance, the diversity of global inter-cluster knowledge networks is positively associated with cluster innovation performance (Boschma 2005).

The positive influence of path dependence on cluster innovation performance (theoretical perspective 5, hypotheses 11 & 12) is also observed (Crescenzi and Jaax 2017), however the results provide weak support for the assumption that more mature sectors like health technology have stronger path dependence (Martin and Simmie 2008). In the emerging and fast-growing sustainable energy technology sector past innovation performance is also statistically significant, accounting for around 33% of model explanatory power. This is less than the 49% explanatory power in the more mature health technology sector, but the difference is not very large.

Table 8.1: Theoretical perspectives (hypotheses) and empirical findings.

Theoretical Perspectives (with Hypotheses)	**Empirical Findings**
1a. Growth of technology clusters mainly in Asia (global shift) **(H1)**	Growth has taken place in Asia and also in other continents. Global shift to South Korea and Taiwan occurred before 2000s but has extended to China.
1b. A mature sector (e.g. health technology) has more agglomeration and a denser global knowledge network as compared to an emerging sector (e.g. sustainable energy technology, **H2**)	Partially supported, however the medical devices sub-sector is facing (very) low agglomeration
2a. Agglomeration economies offer advantages to cluster innovation performance **(H3 & H4)**	Supported, advantages are found at the local scale of the cluster. However disadvantages are found at the regional level (in large metropolitan areas)
2b. Corporate research is associated with high cluster innovation performance **(H5)**	Supported

Theoretical Perspectives (with Hypotheses)	**Empirical Findings**
3. Cluster innovation performance is influenced by the national innovation system **(H6)**	Supported, but only in the sustainable energy technology sector
4a. Knowledge inflows and outflow as mediated by MNCs are positively associated with cluster innovation performance **(H7 & H8)**	Supported (health technology outflow)
4b. The diversity and density of global knowledge networks enhances cluster innovation performance **(H9 & H10)**	Diversity is supported, however density is not
5. Path dependence has a positive association with cluster innovation performance, especially in more mature sectors (e.g. health technology, **H11 & H12**)	Path dependence is supported, but weak evidence of stronger path dependence in health technology

The theoretical contribution of the study, as summarized in table 8.1 is based on the estimation results of an innovation performance model developed as part of this study. The model differs from knowledge production functions, especially in terms of its dependent variable, which is a productivity indicator consisting of: knowledge output (patent citations) divided by input (inventors). Because of this procedure, the model fit of the innovation performance model appears weaker when compared to many knowledge production functions. However, this is because the greatest source of variation, input, has been removed from the model.

In the cluster innovation performance model up to 60% of variation is accounted for by past cluster innovation performance (path dependence). Path dependence includes all conditions which develop or accumulate over time, including the national innovation system, agglomeration and knowledge networks. The other 40% that is unaccounted for by the cluster innovation performance model may be due to the inherent uncertainties of innovation outcomes as well as methodological limitations, such as the exclusion of local cultural or policy factors from the model, for example, risk-taking or local policy initiatives. With regard to innovation uncertainty, the number of citations a patent receives and the long-term value of a patent or technology cannot be known beforehand because research outcomes and future technological paths are uncertain. Therefore R&D that seems promising at one point in time may not produce the expected innovation outcomes and corresponding patent citations (Popp et al. 2013; Cohen 2021). Methodological and measurement issues are addressed in more detail in section 9.3, but it is important to note that bibliometric indicators are ultimately proxies for the innovation activities they describe, and thus some degree of measurement uncertainty will always exist.

The research results also differ between the chosen sectors and study periods. Because the health technology sector is mostly similar to the reference high technology sector in terms of its spatial distribution, knowledge networks and the factors associated with cluster innovation performance (see also chapter 7), the research results may also be applicable to other high technology sectors. However even within the health technology sector there are notable differences between the medical life sciences and medical devices sub-sectors (e.g. clustering rates), suggesting that significant sectoral variations do exist, even in mature high technology sectors in the same industry group. Therefore generalizations should only be made with great caution.

8.5.4 Policy: Cluster Benchmarking and Application of Innovation Performance Model

The policy relevance of the research can be divided into two parts: first, the relevance of the research methodology for data collection for policy monitoring is described. Second, the analysis based on a preliminary framework of cluster development strategies is briefly addressed. The results on policy relevance are exploratory, as the main contribution of the research lies in the empirical domain.

With regard to monitoring, the data and methodology used to identify technology clusters provides insight into the spatial scale and density of innovation activity. Sometimes a technology cluster covers a single city, but frequently a cluster covers multiple cities and occasionally it crosses state or national boundaries. This situation suggests that the spatial scale at which cluster policy should be carried out also varies: cluster policy could involve a local authority of a single city (Van Geenhuizen and Nejabat 2021) or a regional authority, but it could also combine multi-level spatial administrative units through a collaborative framework involving multiple cities, regions or even countries (Park 2014). Especially if a cluster covers *multiple* spatial administrative units, there is the challenge of sufficient collaboration and coordination to guarantee a good alignment of policy-making. In this sense, the first contribution of the study (methodology) to cluster policy-making, is support in identification of the spatial boundaries of a technology cluster, and the policy makers that operate within them. It is also possible to "zoom in" on certain areas of a larger cluster, although a lack of detailed patent address data can limit the scale at which this is possible.

In addition to identifying a cluster, the methodology offers a useful tool for measuring and tracking the creation and growth of technology clusters, their knowledge networks and key innovation actors, all on a worldwide scale using patent data. The cluster identification methodology appears to be sufficiently reliable and its underlying principles have been accepted in the academic literature (Alcácer and Zhao 2016; Stek 2019, 2021). Also, the information about clusters obtained from patent data can help policy-makers benchmark cluster innovation performance and growth, such as that of technology clusters in the same sector or sub-sector in European Union and in smaller groups of collaborating countries, like Scandinavia. This information can also be part of public or public-private location decisions for new research facilities and infrastructure construction. For example: the development and testing of new types of sustainable energy, such as hydrogen, fuel cells and related product applications may be promoted in a particular cluster. Of course, cluster patent data need to be supplemented with statistical studies, and surveys among decision-makers, firms and citizens in the region.

With regards to the components required in cluster policy, a simple framework for cluster development strategies is compared with the research findings of the study (Brenner and Schlump 2011; Uyarra and Ramlogan 2012; Njøs and Jakobsen 2016). In line with the theoretical perspective of the study, policy relevance is explored from a regional policy and evolutionary perspective with some insights into national economic-technological policy.

The empirical findings of the study support the view that "monocropping" (regional agglomeration) and "hubbing" (growing global knowledge networks) can support cluster development, although "hubbing" in more mature sectors may involve inward and outward investment by multinational corporations, rather than inter-organizational research collaboration. A "blending" strategy, which involves developing linkages with other technology sectors in the same region, appears to be more relevant to cluster growth than to cluster innovation performance.

It also appears that local/regional cluster policies alone are often insufficient if attempting to break into mature sectors. In such cases, national policy support is also needed, possibly with additional help of European Union policy. The private sector always plays an important role in cluster development, a view that is confirmed by the empirical findings of this study.

It is important to note that the policy analysis presented in this study does have notable limitations because certain cluster conditions, such as the influence of culture or local and national policy schemes, are unobserved. This is due to the use of patent-based indicators and a simplified research model.

8.6 Conclusion

This chapter has presented a summary of the most important research findings of this dissertation as well as their broader methodological, empirical, theoretical, and policy contributions. The organic cluster identification methodology demonstrates a new approach to analyzing technology clusters, enabling them to be characterized in terms of spatial distribution, size and size distribution, cluster actors, knowledge network links, and cluster innovation performance *on a global scale*. This approach also enables the estimation of a novel cluster innovation performance model using indicators derived from patent information.

The empirical results from this new methodological approach provide novel quantitative insights into global and sectoral differences. The descriptive analysis reveals the dynamic spatial distribution of the fast-growing sustainable energy technology sector and its inter-cluster knowledge networks. The explanatory analysis provides a more detailed perspective on agglomeration advantages and disadvantages, revealing that they act at different spatial scales (local and within 200 km range). It also reveals several noteworthy differences between the sustainable energy technology sector and the health technology and reference sectors in terms of the association between cluster innovation performance and adjacency, corporate research, the national innovation system, and knowledge outflow. These differences can be attributed to the different growth trajectories and to a lesser extent, the involvement in socio-technological transitions of the sustainable energy technology sector. The differences between sustainable energy technology and the more mature health technology and reference sectors could be representative of general differences between emerging and mature high technology sectors.

From a policy perspective, the new methodology offers a suitable tool for the identification and monitoring of technology clusters. The empirical results offer support for "monocropping" and "hubbing" cluster development strategies with limited support for a "blending" strategy (Njøs and Jakobsen 2016). The results also emphasize the importance of private sector involvement and the need for national (or European) innovation strategies, to enable clusters to establish themselves in new technology sectors. However, as the innovation performance model tends to provide limited explanation, conditions beyond the model and beyond the sector and economic system also need to be taken into account.

In the next chapter (chapter 9) the limitations of the research are discussed, and a reflection on the research results is offered, along with specific suggestions for future research.

Chapter 9

Reflection and Future Research

9.1 Introduction

The research in this dissertation has sought to address knowledge gaps on sustainability technology sectors concerning spatial distribution and network patterns, dynamics over time, and spatial differences in innovation performance. A novel methodological approach has yielded novel empirical results, which reinforce or further clarify existing theories about agglomeration and socio-technological transitions, and provide practical descriptive insights into the health technology and sustainable energy sectors. However, the results also raise questions about the precise nature of socio-technological transitions in both sectors, the ability to model cluster innovation performance, and the causes of spatial dynamics.

This concluding chapter presents a reflection on the research results (section 9.2), a discussion of the research limitations (section 9.3), recommendations for future research (section 9.4), and a conclusion of the overall research (section 9.5).

9.2 Reflection

The research findings raise important themes in three conceptual areas which deserve further reflection. The first theme concerns the concept of innovation performance, which, depending on how it is defined, leads to different interpretations of the research findings (subsection 9.2.1). The second theme concerns the underlying causes of global shifts and the spatial distribution of innovation performance, which may be caused by factors that have generally remained beyond the scope of this study (subsection 9.2.2). The third theme concerns the nature of emerging sectors, including those involved in socio-technological transitions, and the extent to which they differ from mature and other emerging sectors that are *not* involved in socio-technological transitions (subsection 9.2.3).

9.2.1 Innovation Performance as a Concept

As mentioned in the introduction of this dissertation, innovation performance can be concisely defined as the ability to generate new knowledge and apply it in an economically useful way

(Acs, Anselin, and Varga 2002; Tidd, Bessant, and Pavitt 2005; Binz and Truffer 2017; Crescenzi and Rodríguez-Pose 2017). In this study innovation performance has been further defined as an *efficiency* parameter, which measures the value of innovations generated in the cluster relative to the number of researchers from the cluster, i.e. the productivity of researchers. This is a different approach to measuring and operationalizing innovation performance compared to other innovation studies that use patent count data (Ponds, Oort, and Frenken 2009; Crescenzi and Jaax 2017) and has important implications for the research. These implications can be summarized as follows: the focus of this study is on measuring the value that innovation activity creates, as measured by the number of patent citations received (a proxy for the scientific and market value of a patent), and on modeling differences in innovation *efficiency*.

The modelling of innovation performance in this study reveals statistically significant relationships between cluster innovation performance and agglomeration, knowledge networks and path dependence. In the case of sustainable energy technology, there is also correlation between cluster innovation performance and the national innovation system. In the mature health technology sector path dependence has the largest explanatory power (adj. R^2 of 0.490, other factors adj. R^2 of -0.001 to 0.143), which is also the case in the reference high technology sectors. In contrast the explanatory power of all four factors, including path dependence, are relatively close to each other in the emerging sustainable energy technology sector (adj. R^2 of 0.249 to 0.334). These results raise two important questions: (i) why is a significant part of cluster innovation performance variation unexplained? and (ii) what causes the significant differences in model explanatory power? Some possible answers are discussed below.

Besides the possible absence of certain model indicators (see discussion in section 9.3), there could be an additional and more fundamental reason for the lack of model explanatory power. Based on an extensive literature review, Ter Wal and Boschma (2011) conclude that agglomeration and knowledge network conditions play an especially important role during the *early stages* of a sector or cluster's development, but that their influence declines over time. The conclusion fits with the observation that in the sustainable energy technology sector, which is in an *early* development stage, agglomeration and knowledge networks both play a relatively important role. In the mature health technology sector, their association with innovation performance seems much weaker.

If the role of agglomeration and knowledge networks in mature sectors is smaller, then what else could explain variation in cluster innovation performance? One possibility is that these differences are caused by the dominant technological specialization or specializations of the cluster, which Popp et al. (2013) notes heavily influence patenting success. During periods of stable technological development, the success of a particular technological specialization, may persist over long periods of time and technological expertise may accumulate. This explains the strong influence of path dependence in mature high technology sectors. From this perspective, the (in)ability to enter the "right" technological specialization(s) at the right time may be the most important condition in explaining a cluster's long-term innovation performance. For example, Popp et al. (2013) observe that from the 1971 to 1991 fuel cells saw an increase in patent citations and patent output, whereas nuclear energy patenting and citations were stagnant, and wind patents and citations vary strongly over time, peaking in 1971 and 1991. Viewed from the perspective of hindsight, it is highly likely that a fuel cell technology cluster would have performed far better over the long term than a nuclear energy technology cluster.

It can thus be argued that the influence of agglomeration and knowledge networks on innovation performance is smaller than expected, both in mature and emerging sectors. Instead, innovation performance may become more sensitive to other factors, such as policy decisions, the cluster organizations' technological strategy and the direction of technological change (Deloitte 2016; Isaksen 2016; Langhelle, Meadowcroft, and Rosenbloom 2019), all conditions that were outside of the relatively simple cluster innovation performance model used in this study.

9.2.2 Global Shift or Local Shift?

The study's research findings are ambiguous concerning the extent to which a "global shift" in innovation activity is taking place towards Asia (Dicken 2007; Miao et al. 2018). Although many fast-growing clusters are found in Asia, some are also found in the United States and to a lesser extent, in Europe. The United States and Europe see a greater formation of new clusters, especially in the sustainable energy technology sector, while Asia sees growth in a smaller number of large and very large clusters. The global shift of economic activity towards Asia, including innovation, is seen as a the result of 'push' and 'pull' factors (Dicken 2007). Globalization is driving increasing competition and enables international investment in R&D (Audretsch, Lehmann, and Wright 2014; Locke and Wellhausen 2014). On the other hand, heavy domestic investment by Asian countries in higher education, research infrastructure, R&D incentives to attract foreign investment (notably in Singapore), and domestic policies to stimulate innovation by local firms (notably in Taiwan and South Korea), have supported rapid growth in innovation activity (Dicken 2007; Ahn 2017; Miao et al. 2018).

Especially in the emerging sustainable energy technology sector, "pull" factors seem to exist at the level of individual clusters, whereby local policies and incentives cause a "local shift" to a particular location, which creates or supports the growth of a local technology cluster (Steen and Hansen 2018; Van Geenhuizen and Holbrook 2018; Van Geenhuizen and Ye 2018). This process is not restricted to Asia: it is found in Europe and North America as well, although it appears to be weaker in more mature sectors. In the United States a weak trend of medical research shifting to smaller cities has been observed in recent years (JLL 2012; Giuliano, Kang, and Yuan 2019). In Europe, during the early phases of the medical devices sector's development, there has been a tendency for new clusters to emerge in small cities with existing capabilities in related fields, such as fine mechanical manufacturing (Klein, Banga, and Martelli 2015). Sustainable energy technology clusters, such as wind turbine clusters, have established themselves in relatively remote locations to take advantage of specific natural resources, such as windy weather (Kamp, Smits, and Andriesse 2004; Van Geenhuizen and Holbrook 2018).

From a broader policy perspective, these observations suggest that the early development phase of a sector is a critical time during which cities or regions can and do position themselves to attract certain industries and related innovation activity. As a sector becomes mature, opportunities to bring about a "local shift" appear to diminish unless they are part of a broader national technology policy (Lee 2016).

Although they occur in the context of broad global trends, the creation and growth of clusters is ultimately the result of local characteristics, such as the availability of research institutions, relevant knowledge and expertise, talent, cost, quality of life, policy incentives, etc. In this sense, "global shifts" signify broad trends, which become "local shifts" at the level of individual technology clusters.

9.2.3 Socio-Technological Transitions and Emerging Sectors

Although both viewed as part of a socio-technological transition, the two sustainability technology sectors are in different development stages and appear to be experiencing socio-technological transitions of a different nature (Geels 2012; Geels et al. 2017; Ohta 2019). The sustainable energy technology transition involves a shift in the energy and transportation system towards low or zero-carbon alternatives to address the challenge of climate change (Geels 2012; Geels et al. 2017). In the healthcare sector socio-technological changes aim to enhance affordability and effectiveness and to improve access to all people (Chen 2009; Škalko-Basnet 2014; Deloitte 2016; Lybecker 2016; Mentesana et al. 2017). As a result of ageing societies socio-technological changes are also needed in how healthcare is organized, financed, and delivered (World Health Organization 2004; Ohta 2019).

The changes taking place within the sustainable energy sector can be seen as being more disruptive than those in the healthcare sector because sustainable energy technologies have the potential to make carbon-based energy sources obsolete, threatening large parts of the fossil fuel industry. A photovoltaics installation or wind turbine facility does not require a fuel input, and electric or hydrogen-powered vehicles require a completely different refueling infrastructure and related technologies (Tidd, Bessant, and Pavitt 2005; Holbrook, Arthurs, and Cassidy 2010; International Energy Agency (IEA) 2019d). Profound changes in market structure are set to take place: households may transition from being energy consumers in a centralized system to energy producers *and* consumers in a decentralized smart grid energy system (IEA PVPS 2016; Geels et al. 2017). In this sense, the sustainable energy technology sector is clearly path creating, leading to potential path breaking for carbon-based energy sectors (Martin and Simmie 2008).

While groundbreaking technological changes are taking place in the health technology sector, such as the discovery of new biologic drugs, which are coupled to new diagnostics tools such as genome analysis (Škalko-Basnet 2014; Lybecker 2016; Mentesana et al. 2017), they do not fundamentally change the *business model* of pharmaceutical firms or medical device producers (Johansen and Van den Bosch 2017; Mentesana et al. 2017; Ohta 2019). Instead, the business models for the organization and financing of medical care and living arrangements for the elderly are the areas where sustainability and other transitions are taking place (Johansen and Van den Bosch 2017; Ohta 2019). This is different from the socio-technological transitions in sustainable energy technology, whereby changes in technology will often require changes in the business model, the behavior of consumers, government policies and power between different market participants (Geels 2012; Geels et al. 2017). It thus appears that the sustainable energy technology sector is facing a true *socio-technological* transition, causing a fundamental shift in business models and technology. The health technology sector seems to be undergoing two separate transitions: a *social* transition due to ageing and the need for social inclusion, and a *technological* transition due to advancement in science. But the two trends appear less connected than in the sustainable energy sector, and seem to have less impact on existing healthcare business models.

9.3 Research Limitations

The model design, data, and methodology used and the selection of sectors and time periods impose some noteworthy research limitations. The model design is based on using patent data, which provides global coverage, but this modeling approach also excludes the use of data sources that are only available locally or nationally (subsection 9.3.1). The use of patent data also imposes some methodological challenges in terms of how patents are counted and clusters are identified (subsection 9.3.2), and the limitations arising from the chosen sectors and time periods (subsection 9.3.2).

9.3.1 Model Design

The most important limitation of the model design is that cluster conditions are measured using patent data, which is a simplification of reality and means that some concepts are only measured indirectly or cannot be measured at all. This limitation influences the kinds of conditions that are incorporated in the model design and the way in which they are measured. For example, the importance of social capital and entrepreneurship have been noted in the literature (Fazio and Lavecchia 2013; Lange 2016; Vaan, Frenken, and Boschma 2019; Malerba and McKelvey 2019) but are addressed within the study as part of agglomeration economies and path dependence (social capital) and corporate research (entrepreneurship). Also excluded from the model are internal cluster linkages, such as research collaborations between universities and firms within the cluster. This decision was taken due to the lack of patent data, as university-industry co-applications for patents are rare in most sectors (health technology being a notable exception). In this sense the use of patent data imposes certain model limitations, which must be weighed against the benefit of data at the cluster scale that is global in its scope, and which can be frequently updated with new patent data.

9.3.2 Patent Data

Although the use of patent data has many benefits, including its availability over long periods of time and the ability to identify specific technological sectors, its use also carries with it a number of potential pitfalls and limitations (Pavitt 1985; Kleinknecht, Van Montfort, and Brouwer 2002; Lanjouw and Schankerman 2004; Boeing, Mueller, and Sandner 2016). The cluster identification methodology, including the choice of the original patent data source and the method of optimizing cluster identification parameters, has been carefully discussed in the methodology chapters (chapters 3 and 4). Below is a discussion of the limitations of the chosen home bias correction factor and the challenges of comparing sectors with different patenting propensities.

The cluster identification method used in this study is based on a single patent database: that of the United States Trademark and Patent Office (USPTO). A correction for the home bias effect is therefore needed and has been carried out by analyzing the differences in patenting and citation frequencies between the United States and Japan. Here, Japan represents the world outside the United States because Japan, like the United States, is a highly technologically advanced country and shows a high degree of technological similarity with the United States (Toivanen and Suominen 2015). While this approach seems reasonable, patenting frequencies are also influenced by political and economic conditions such as trade and investment flows, technological collaboration and intellectual property right protection regimes (Yang and Kuo 2008). The correction factor therefore also incorporates the close economic and political relationship that exist between Japan and the United States (Yang and Kuo 2008). This could mean that patenting in advanced economies which have an adversarial or very minimal relationship with the United States, is underestimated by a correction factor based on Japan.

In practical terms, the current technological rivalry between the United States and China means that political factors may influence the patenting frequency of Chinese inventors and organizations in the United States. However during the 2000-2011 study period China was still well behind the United States in terms of its technological capabilities (Toivanen and Suominen 2015; Boeing, Mueller, and Sandner 2016). The number of Chinese technology clusters in the study sample is also low, typically at around 5% or less, depending on the sector. This means that the influence of Chinese technology clusters on the overall study results is relatively small. A similar argument can be made for Russia, which is behind China in terms of total innovation output in most technological fields. Although a political bias could influence the spatial distribution and agglomeration analysis of the study and parts of the cluster innovation performance model (dependent variable based on patent citations), this situation does not appear to influence the current study. Furthermore, network indicators, the clustering rate, and path dependence would also be less affected, because these indicators are typically less size-dependent.

A second limitation of the use of patent data is that patenting frequencies between sectors can vary by 10 or 20 times based on the different patenting propensities of the sectors (Kleinknecht, Van Montfort, and Brouwer 2002; Tidd, Bessant, and Pavitt 2005). This means that in sectors with few patents relative to their research activity, patents provide less information about ongoing research activity: each organization or collaboration may produce only a few patents or none at all. The impact of this difference on the present study seems limited, because although the health technology sector had about three times more patents than the sustainable energy technology sector in 2008-2011, the explanatory power of healthcare innovation performance models was not consistently higher than that of sustainable energy technology.

9.3.3 Sector and Time Period Selection

The time period selected in this study is based on the most recent 12-year period for which complete patent grant data were available when the study was undertaken (2018). This selection is not based on the period when certain sectors first emerged or reached a state of maturity. Because of the importance of a sector's development stage on its innovation process, a different selection of time periods could have provided additional insights into the different emerging stages of the two sectors (Martin and Simmie 2008; Ter Wal and Boschma 2011; Frenken, Cefis, and Stam 2015).

If the health technology sector had been analyzed starting from an earlier period when it was undergoing rapid growth (e.g. 1980s and 1990s), this phase could have been compared to the rapid growth phase of the sustainable energy technology sector during 2000-2011. A comparison of the rapid growth phases could have provided further insight into the unique position of the sustainable energy technology sector and its role in the socio-technological transition towards a low-carbon energy system (Geels et al. 2017). The sector comparison in the present study is limited by the fact that both sectors appear to be in different growth phases. However, the advantage of selecting the same time period is that there are no differences in the world economic situation and development level of other technologies, such as the trend of digitization, level of economic globalization, etc. Such differences could have influenced a sectoral growth phase comparison that is 10 or more years apart.

A second limitation is the time period itself (2000-2011). Since 2011, there has been further growth in R&D output in East Asia, and China in particular (Miao et al. 2018). Some sustainable energy technologies, such as photovoltaics, have become cost-competitive when compared to conventional carbon-based energy generation technology such as coal (International Energy Agency (IEA) 2019c). This suggests that the volume of sustainable energy patenting has also increased and that the sector is entering a mature development phase. The current COVID-19 pandemic has also likely increased R&D output in the medical life sciences.

One way of studying more recent time periods is to use patent application data instead of patent grant data, although this comes with a trade-off. First, not all patent applications are eventually granted and so the patent application data set may contain more lower quality inventions. Second, because patent applications are new, insufficient time has passed for them to be cited by other patents and the innovation performance indicator cannot be calculated. However, other cluster indicators which describe knowledge networks and agglomeration can be derived from patent applications. In that sense, patent applications may be useful for the purpose of monitoring technology cluster development, but less useful for analyzing cluster innovation performance.

9.4 Recommendations for Further Research

The main limitations identified in this study center on the model design, the use of patent data and the time period selection. Based on these limitations and the reflections noted above, the following areas of research should be explored in future:

1. Further research into the global spatial distribution, knowledge network and cluster innovation performance dynamics after 2011. this study could capture trends such as the rise of China and the growth of other emerging economies like Brazil and India, whether R&D growth remains concentrated in large cities, or whether smaller cities develop further, and whether the pervasiveness of internet-related technologies since the COVID-19 pandemic influences the spatial and knowledge network patterns of technological innovation.

2. The model design is limited by the incorporated cluster characteristics because it had to rely on patent data to provide a global overview of technology clusters. Through this simplified design important factors related to the innovation actors of the clusters (such as individual inventors or institutions), local networks, entrepreneurship culture, and government policies and incentives are excluded or only partially addressed. These factors could be included in future research through selected cluster case studies that provide additional depth and local context to the global research results obtained from bibliometric and non-bibliometric data sources.

3. The sustainability technology sectors analyzed in this study contain a diverse set of sub-sectors which in turn consist of many different sub-specializations. A more detailed study of these sub-sectors and sub-specializations may provide a better understanding of emerging and declining technological specializations, and their influence on the broader innovation performance and development pattern of the sustainability technology sectors included in this study. This may also include studies at the lowest level, namely of principal inventors at multinational corporations or universities, and follow the spatial development (which cities/countries) of where their knowledge (patents) is brought to market.

4. The impact of socio-technological transitions, which disrupt existing business models as compared to other emerging sectors, could be explored further by applying the research

methodology to different study periods and sectors, such as internet-related technologies, the emergence of more energy-efficient steel mills, energy-efficient lighting, or 3D-printing technologies, which are disrupting manufacturing. This could provide further insight into the influence of socio-technological transitions on technology sectors and the emergence of sectors in general.

5. From a methodological perspective, the foreign patenting patterns of different countries could be further explored. While Yang and Kuo (2008) show the influence of trade and regulatory factors on foreign patenting activity, and Toivanen and Suominen (2015) show differences in countries' technological sophistication (which is also seen as influencing foreign patenting), it is not clear how large these influences are. Furthermore, technological distance and trade relationships are evolving, especially between Asian countries such as China and South Korea, in their relationships with each other and with the United States and Europe. Observing such changes could lead to an improved patent and citation correction factor, but changes in foreign patenting and the factors that cause them would also provide new insights into the technological-economic relationships between countries.

6. From a policy perspective, the current research largely excludes the role of policy in cluster innovation performance. However in certain sectors or parts of the world, in which strong cluster policy networks exist, it may be feasible to collect internationally comparable data about cluster policies. This data can then be incorporated into a cluster innovation performance model. This approach would enable quantitative research into the effects of different cluster policies on innovation performance, and could provide insights into *how* innovation policies should be formulated to achieve their intended outcomes. At a more practical level, there may also be value in studying how policy makers and other cluster stakeholders perceive the cluster (heat) maps and cluster indicators presented in this study and how these tools can enhance policy making and policy coordination in real life. A solid empirical foundation and analysis for the actual implementation of the research results in practical policy-making, are also required.

9.5 Conclusion

Despite some limitations, important conclusions can be drawn on the basis of the research presented in this dissertation. Technology clusters are conceived as the main spatial units at which innovation activity takes place and are closely connected to other clusters via global knowledge networks, and this is also the case in sustainability technology sectors, although to varying degrees. In this context, the "organic" cluster identification approach enables a more accurate identification of technology clusters and inter-cluster knowledge networks, for multiple sectors, and on a global scale. This approach not only provides a global map of sustainability technology sector innovation performance for several time periods, but also an extensive database of cluster characteristics for multiple sectors.

A descriptive analysis of cluster spatial distribution provides a detailed perspective on "global shifts" in innovation performance, which are increasingly towards China, South Korea and Taiwan, and also towards some clusters outside these countries, including in Europe. In addition, there appear to be trends of "local shifts" within countries or regions.

A quantitative exploratory analysis of cluster innovation performance provides a more detailed perspective on the relationship between innovation performance and agglomeration, knowledge networks, and path dependence. In addition to demonstrating an association between these factors, the strength of association is also shown. Noteworthy differences between the sustainability technology sectors, in terms of their spatial dynamics and the conditions associated with cluster innovation performance, suggest that the sustainability transitions they are involved in are also of a different type or magnitude. The sustainable energy technology sector is involved in a transition that requires fundamental changes in energy and transport business and distribution models.

The similarities and differences between the sustainability technology sectors also suggest that different policies should be adopted for these sectors. The rapid cluster creation in the sustainable energy technology sector, or the lack of clustering in the medical devices sector, show that a deep understanding of sectors, and tailored policy responses, are needed.

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Appendix A

Cluster Indicators and Cluster Identification

A.1 Assignee Classification

Identifying government assignees is facilitated by the USPTO's classification of assignees, which distinguishes between (US and Foreign) Corporation, Individual and Government.

However universities are classified as both company and government and therefore there is some overlap between privately-owned patents and university-owned patents. To identify university patents a word list is used which is developed from the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) which does classify university assignees (Du Plessis et al. 2009) (see also: https://www.ecoom.be/en/EEE-PPAT).

The word list below is tested on a data sample from the EEE-PPATT table and this yields a success rate of 96% in identifying universities, with 4.7% false positives (non-universities identified as universities) and 3.8% false negatives (universities not identified as universities). Patents classified as a university are added to the total number of university patents (PAT_{UNI}).

The following words and phrases are used to identify an assignee as a university: *ecole, polytechn, universit, hochschule, universid, institute of technology, school, college, georgia tech, academ, penn state, k.u. leuven, politec, higher education, univ., rwth aachen, eth z, kitasato, institute of medical, k.u.leuven, cornell, purdue, institute for cancer, institute of cancer, acadaem, univerz, karlsruher institut, technion, cancer institut, des sciences appliq, alumni, educational fund, hoger onderwijs, postech, politechn, institute of science, virginia tech, eth-z, yeda research, hadasit, board of regents, instituto cientifico, ntnu technology, tudomanyegyetem, uceni technick, universt, alumini, suny, ucla, yliopisto, doshisha, insitute of technology, univsers, kaist, szkola, egyetem, univerc, skola, korkeakoulu, unversit, instituto superior.*

The word list includes parts of words that denote a university and some common spelling errors (e.g. 'univsers,' 'insitute of tehcnology'), names of specific institutions that patent frequently but which lack the name university (e.g. 'UCLA,' 'KAIST'), names of foundations affiliated with certain universities (e.g. 'Yeda Research') and parts of words that denote a university.

A.2 Sector Identification (Reference High Technology Sectors)

Table A.1: High-technology reference sectors with their respective ISIC or CPC identification classes.

Sector Name	**Identification Classes**
Aerospace	ISIC group 303
Biotechnology	CPC class A01H1/00, A01H4/00, A61K38/00, A61K39/00, A61K48/00, C02F3/34, C07G11/00, 13/00, 15/00, C07K4/00, 14/00, 16/00, 17/00, 19/00, C12M, C12N, C12P, C12Q, C12S, G01N27/327, G01N 33/53, 33/54, 33/55, 33/57, 33/68, 33/74, 33/76, 33/78, 33/88 and 33/92
Chemicals and chemical products	ISIC division 20
Computer, electronic and optical products	ISIC division 26
Defense	ISIC group 252 & 304
Electrical equipment	ISIC division 27
Machinery and equipment	ISIC division 28
Motor vehicles	ISIC division 29
Nanotechnology	CPC class B82B & B82Y
Pharmaceuticals	ISIC division 21

A.3 Cluster Identification 'Heatmap'

The following notes expand on the observations and analysis presented in section 4.5.1 of chapter 4.

Compared to the pre-determined cluster boundaries and the organic clustering algorithms by Alcácer and Zhao (2016), the heatmap algorithm developed in this study performs well. The share of co-inventors located 16-32 km from each other and found within the *same* cluster (D_{dif}) is 66% for the heatmap algorithm (this study) compared to $D_{dif} = 59\%$ for the organic clustering algorithm by Alcácer and Zhao (2016) (see also table 4.5). This suggests that a heatmap approach is preferable to the approach taken by Alcácer and Zhao (2016), which involved assigning patents to specific cities and merging cities located in close proximity into a single cluster.

A heatmap of Western Europe that illustrates the results of the cluster identification method used in this study is shown in figure A.1. Dark points are areas with high concentrations of patent output. The map shows a number of urban corridors of high innovation activity, including in Southeast England (London), the Western Netherlands (Amsterdam), the Belgian city triangle of Brussels, Ghent and Leuven, and an almost continuous pattern of 'dark spots' stretching from Frankfurt south towards Zurich and then southwest towards Lyon. These patterns show some of the the challenges in identifying clusters that exist in close proximity: are they part of a single macro-cluster or should they be seen as separate clusters? Heatmaps are also available for the Eastern United States (figure A.2), showing the urban corridor stretching out around New York, and Northeast Asia (figure A.3), with an urban corridor centered on Tokyo and extending westward towards Osaka.

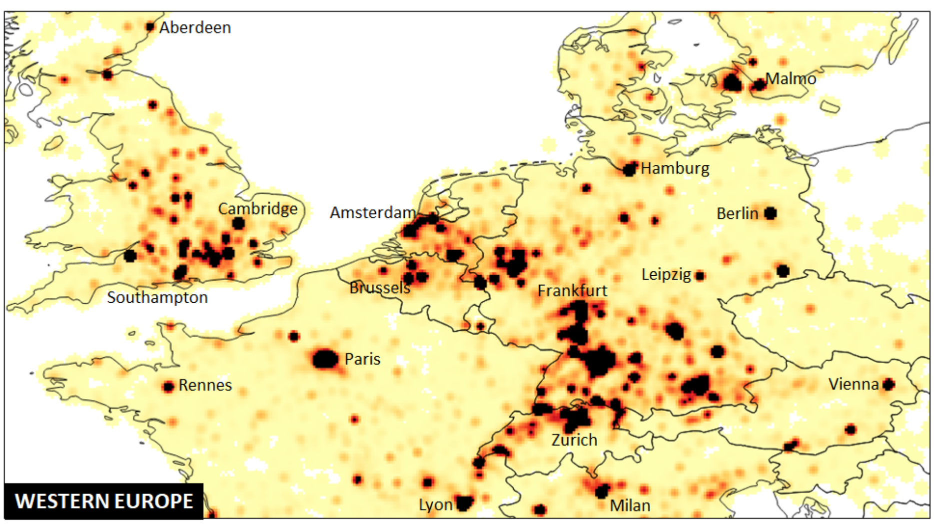

Figure A.1: Patent output heatmap, Western Europe.

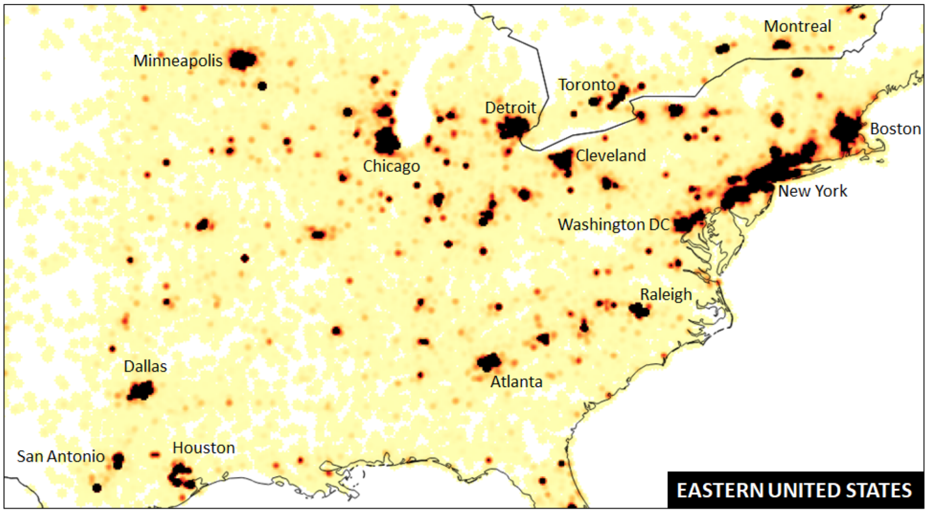

Figure A.2: Patent output heatmap, Eastern United States.

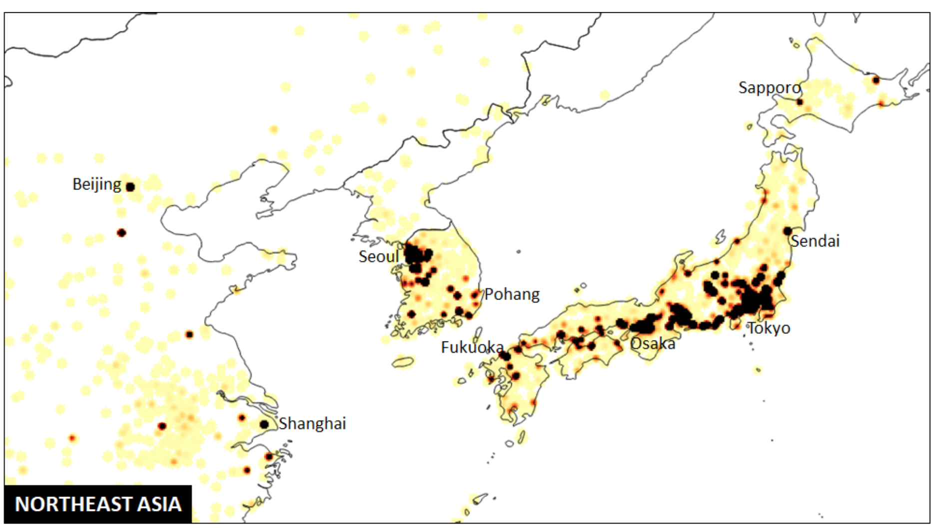

Figure A.3: Patent output heatmap, Northeast Asia.

A.4 Clustering Indicators by Sector

Table A.2: Clustering indicators for all sectors in this study.

Sector	A_{max}	D_{same}	D_{dif}	n	P_{total}	$PS_{cluster}$
Aerospace	8,351 km^2	99%	62%	118	16,095	64%
Chemicals	26,539 km^2	100%	61%	168	140,255	75%
Computer and electronics	19,964 km^2	100%	63%	154	527,516	85%
Defense	3,542 km^2	90%	65%	55	4,790	34%
Electrical equipment	16,074 km^2	99%	63%	143	92,310	73%
Machinery and eq.	28,189 km^2	100%	59%	167	102,793	67%
Motor vehicles	20,147 km^2	100%	45%	108	31,908	64%
Pharmaceuticals	22,377 km^2	100%	63%	149	83,805	72%
Biotechnology	3,542 km^2	89%	90%	57	26,981	25%
Nanotechnology	6,193 km^2	100%	71%	57	10,022	61%
Medical life sciences	15,890 km^2	99%	72%	146	24,124	73%
Medical devices	3,542 km^2	100%	60%	71	39,948	25%
Electric vehicles	6,204 km^2	100%	57%	35	5,096	71%
Energy storage	3,917 km^2	99%	51%	17	2,847	26%
Fuel cells	5,650 km^2	100%	61%	17	1,716	50%
Hydrogen technology	2,570 km^2	98%	86%	14	954	25%
Photovoltaics	5,363 km^2	97%	46%	21	5,521	44%
Wind turbines	2,014 km^2	96%	98%	24	2,775	31%

Appendix B

Cluster Innovation Performance Model

B.1 Model Development

Model estimations to further develop the cluster innovation performance model are presented in the tables below. For description and intepretation, see section 3.6.2.

Table B.1: Influence of sectoral knowledge base on innovation performance using dummy variable (scientific knowledge base). Dependent variable: innovation performance (log).

Indicators	Health Technology	Sustainable Energy	Reference High Technology
Knowledge Base (dummy)	-0.39 (0.38)	-2.3 (0.66)***	0.33 (0.17)**
Constant	1.5 (0.37)***	3.9 (0.63)***	1.8 (0.088)***
Adjusted R^2	0.004	0.091	0.003
Clusters (n)	219	167	1180

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.2: Agglomeration models for health technology.

Indicators	Linear Model	Log-Log Model	Log-Quadratic Model
Cluster size	45. (19.)**		
Adjacency	-2.0 (0.95)**		
Regional specialization	2.7 (1.5)*		
Corporate research	0.59 (0.27)**		
Cluster size (log)		5.2 (1.3)***	
Adjacency (log)		-0.25 (0.13)*	
Specialization (log)		0.31 (0.15)**	
Corporate research (log)		0.29 (0.079)***	
Cluster size ($\log^2$)			-1.2 (0.28)***
Adjacency ($\log^2$)			0.062 (0.052)
Specialization ($\log^2$)			-0.10 (0.050)**
Corporate research ($\log^2$)			-0.17 (0.037)***
Knowledge base (dummy)	-0.41 (0.42)	-0.053 (0.11)	-0.082 (0.11)
Constant	0.83 (0.31)***	12. (3.0)***	6.2 (1.5)***
Adjusted R^2	0.015	0.089	0.091
Adjusted $/DeltaR^2$	0.011	0.085	0.087
Clusters (n)	219	219	219

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.3: Agglomeration models for sustainable energy.

Indicators	Linear Model	Log-Log Model	Log-Quadratic Model
Cluster size	100. (84.)		
Adjacency	-51. (29.)*		
Regional specialization	5.1 (3.9)		
Corporate research	-0.25 (0.97)		
Cluster size (log)		7.0 (2.9)**	
Adjacency (log)		-1.7 (1.2)	
Specialization (log)		0.36 (0.20)*	
Corporate research (log)		0.048 (0.15)	
Cluster size ($\log^2$)			-1.5 (0.64)**
Adjacency ($\log^2$)			0.42 (0.28)
Specialization ($\log^2$)			-0.12 (0.063)*
Corporate research ($\log^2$)			-0.048 (0.070)
Knowledge base (dummy)	-2.1 (0.84)**	-0.96 (0.15)***	-0.95 (0.14)***
Constant	3.8 (1.5)**	14. (7.3)*	7.3 (3.7)**
Adjusted R^2	0.088	0.250	0.252
Adjusted $/DeltaR^2$	-0.003	0.159	0.161
Clusters (n)	167	167	167

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.4: Knowledge network models for health technology.

Indicators	Linear Model	Log-Log Model	Log-Quadratic Model
Knowledge inflow	0.50 (0.57)		
Knowledge outflow	0.46 (0.24)*		
Network reach	0.072 (0.024)***		
Network density	-0.37 (0.34)		
Knowledge inflow (log)		0.059 (0.093)	
Knowledge outflow (log)		0.43 (0.14)***	
Network reach (log)		0.36 (0.067)***	
Network density (log)		-0.17 (0.13)	
Knowledge inflow ($\log^2$)			-0.081 (0.050)
Knowledge outflow ($\log^2$)			-0.24 (0.14)*
Network reach ($\log^2$)			0.12 (0.026)***
Network density ($\log^2$)			-0.034 (0.067)
Knowledge base (dummy)	-0.16 (0.33)	0.083 (0.13)	-0.091 (0.13)
Constant	0.68 (0.26)***	-0.38 (0.16)**	-0.025 (0.13)
Adjusted R^2	0.020	0.143	0.102
Adjusted $/DeltaR^2$	0.016	0.139	0.098
Clusters (n)	219	219	219

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.5: Knowledge network models for sustainable energy.

Indicators	Linear Model	Log-Log Model	Log-Quadratic Model
Knowledge inflow	0.077 (0.14)		
Knowledge outflow	-0.29 (0.66)		
Network reach	0.60 (0.33)*		
Network density	0.34 (0.72)		
Knowledge inflow (log)		0.11 (0.072)	
Knowledge outflow (log)		-0.098 (0.14)	
Network reach (log)		0.27 (0.12)**	
Network density (log)		0.17 (0.12)	
Knowledge inflow ($\log^2$)			-0.075 (0.042)*
Knowledge outflow ($\log^2$)			0.089 (0.054)
Network reach ($\log^2$)			0.016 (0.14)
Network density ($\log^2$)			-0.16 (0.048)***
Knowledge base (dummy)	-2.3 (0.71)***	-1.0 (0.13)***	-1.1 (0.13)***
Constant	3.4 (0.92)***	1.4 (0.16)***	1.3 (0.17)***
Adjusted R^2	0.081	0.296	0.279
Adjusted $/DeltaR^2$	-0.010	0.205	0.188
Clusters (n)	167	167	167

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.6: Interaction model for health technology.

Indicators	Linear Model	Interaction Model
Cluster size (log)	7.6 (1.5)***	
Network density (log)	0.22 (0.11)**	
Size $/cdot$ density		-0.027 (0.046)
Knowledge base (dummy)	-0.17 (0.12)	-0.11 (0.12)
Constant	17. (3.4)***	0.048 (0.14)
Adjusted R^2	0.048	-0.005
Adjusted $/DeltaR^2$	0.044	-0.009
Clusters (n)	219	219

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.7: Interaction model for sustainable energy.

Indicators	Log-Log Model	Interaction Model
Cluster size (log)	12. (3.6)***	
Network density (log)	0.33 (0.12)***	
Size /*cdot* density		-0.10 (0.045)**
Knowledge base (dummy)	-1.0 (0.13)***	-1.0 (0.13)***
Constant	29. (8.2)***	1.3 (0.13)***
Adjusted R^2	0.274	0.256
Adjusted $/DeltaR^2$	0.183	0.166
Clusters (n)	167	167

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

B.2 Health Technology Clusters

Table B.8: Health technology cluster indicator correlation matrix ($n = 219$).

	IVP	PAT	ADJ	SPE	CRP	NSQ	MNC	LAB	NET_S	NET_W	IVP_P
IVP		0.07	-0.05	0.10	0.12*	-0.01	0.15**	0.04	0.12*	-0.03	0.87***
PAT	0.07		-0.07	-0.05	0.12*	0.11	0.09	-0.22***	0.80***	-0.29***	0.11*
ADJ	-0.05	-0.07		-0.09	0.13**	0.10	-0.08	0.19***	-0.12*	-0.04	-0.04
SPE	0.10	-0.05	-0.09		-0.02	-0.29***	0.04	-0.04	-0.03	0.04	0.10
CRP	0.12*	0.12*	0.13**	-0.02		-0.14**	0.06	0.21***	0.12*	-0.07	0.17**
NSQ	-0.01	0.11	0.10	-0.29***	-0.14**		0.15**	0.16**	0.11*	0.02	0.05
MNC	0.15**	0.09	-0.08	0.04	0.06	0.15**		-0.02	0.16**	0.13*	0.16**
LAB	0.04	-0.22***	0.19***	-0.04	0.21***	0.16**	-0.02		-0.17**	0.47***	0.06
NET_S	0.12*	0.80***	-0.12*	-0.03	0.12*	0.11*	0.16**	-0.17**		-0.15**	0.16**
NET_W	-0.03	-0.29***	-0.04	0.04	-0.07	0.02	0.13*	0.47***	-0.15**		-0.09
IVP_P	0.87***	0.11*	-0.04	0.10	0.17**	0.05	0.16**	0.06	0.16**	-0.09	

Table B.9: Medical life sciences innovation performance model estimation results 2008-2011.

Indicators	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size	4.8 (1.2)***				6.0 (1.5)***
Adjacency	0.38 (0.56)				0.18 (0.65)
Regional specialization	0.083 (0.16)				0.045 (0.17)
Corporate research	0.30 (0.090)***				0.25 (0.098)**
National innovation system		-0.43 (0.51)			-0.37 (0.56)
Knowledge inflow			0.065 (0.12)		0.12 (0.14)
Knowledge outflow			0.51 (0.21)**		0.36 (0.20)*
Network reach			0.37 (0.084)***		
Network density			-0.26 (0.19)		-0.075 (0.22)
Past innovation performance				0.59 (0.084)***	
Constant	12. (3.1)***	0.62 (0.85)	-0.32 (0.14)**	-0.45 (0.072)***	15. (4.0)***
Adjusted R^2	0.078	-0.001	0.123	0.366	0.084
Clusters (n)	146	146	146	146	146

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.10: Medical devices innovation performance model estimation results 2008-2011.

Indicators	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size	5.3 (3.0)*				6.2 (3.3)*
Adjacency	-0.16 (0.11)				-0.20 (0.15)
Regional specialization	1.8 (0.57)***				1.7 (0.59)***
Corporate research	0.24 (0.14)*				0.16 (0.16)
National innovation system		-0.81 (0.90)			-1.9 (0.93)**
Knowledge inflow			0.081 (0.17)		0.091 (0.14)
Knowledge outflow			0.37 (0.19)*		0.39 (0.19)**
Network reach			0.34 (0.12)***		
Network density			-0.066 (0.19)		-0.027 (0.19)
Past innovation performance				0.90 (0.099)***	
Constant	15. (6.9)**	1.4 (1.5)	-0.27 (0.27)	-0.93 (0.11)***	20. (7.8)**
Adjusted R^2	0.250	-0.008	0.142	0.773	0.268
Clusters (n)	73	73	73	73	73

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.11: Health technology cluster innovation performance model diagnostics ($n = 219$).

Model	VIF	Shapiro-Wilk W	Shapiro-Wilk p	Breusch-Pagan BP	Breusch-Pagan p
Threshold values	< 2		< 0.10		< 0.10
Control	0	0.38	0	2.51	0.11
Agglomeration	1.1	0.97	0	3.48	0.63
National	0	0.98	0	0.87	0.65
Knowledge networks	1.76	0.95	0	1.37	0.93
Path dependence	0	0.95	0	4.68	0.1
Agglomeration & networks	1.61	0.96	0	5.03	0.83

B.3 Sustainable Energy Clusters

Table B.12: Sustainable energy cluster indicator correlation matrix ($n = 167$).

	IVP	PAT	ADJ	SPE	CRP	NSQ	MNC	LAB	NET_S	NET_W	IVP_P
IVP		0.06	-0.08	0.20**	0.08	0.09	0.07	0.01	0.14*	0.08	0.28***
PAT	0.06		0.06	0.00	0.14*	0.09	-0.01	-0.19**	0.55***	-0.22***	0.03
ADJ	-0.08	0.06		-0.02	0.16**	0.14*	0.09	0.02	-0.03	-0.06	-0.05
SPE	0.20**	0.00	-0.02		0.13	-0.16**	0.04	0.29***	0.07	0.30***	0.07
CRP	0.08	0.14*	0.16**	0.13		0.06	0.12	0.02	0.11	-0.04	0.13
NSQ	0.09	0.09	0.14*	-0.16**	0.06		0.07	0.02	0.12	-0.02	-0.03
MNC	0.07	-0.01	0.09	0.04	0.12	0.07		-0.19**	0.22***	0.13*	0.27***
LAB	0.01	-0.19**	0.02	0.29***	0.02	0.02	-0.19**		0.03	0.55***	0.14*
NET_S	0.14*	0.55***	-0.03	0.07	0.11	0.12	0.22***	0.03		0.27***	0.16**
NET_W	0.08	-0.22***	-0.06	0.30***	-0.04	-0.02	0.13*	0.55***	0.27***		0.26***
IVP_P	0.28***	0.03	-0.05	0.07	0.13	-0.03	0.27***	0.14*	0.16**	0.26***	

Table B.13: Sustainable energy (scientific knowledge base) innovation performance model estimation results 2008-2011.

Indicators	Agglomeration	National	Knowledge Networks	Path Dependence	Agglomeration & Network
Cluster size	12. (6.4)*				17. (6.4)***
Adjacency	-1.7 (1.6)				-1.8 (1.5)
Regional specialization	0.82 (0.54)				0.79 (0.49)
Corporate research	0.040 (0.16)				-0.035 (0.17)
National innovation system		0.83 (0.86)			-0.37 (0.84)
Knowledge inflow			0.30 (0.098)***		0.36 (0.10)***
Knowledge outflow			-0.034 (0.19)		-0.017 (0.18)
Network reach			0.35 (0.18)*		
Network density			0.12 (0.16)		0.30 (0.19)
Past innovation performance				0.37 (0.095)***	
Constant	26. (16.)	-1.4 (1.4)	0.52 (0.19)***	-0.35 (0.14)**	38. (16.)**
Adjusted R^2	-0.006	-0.004	0.119	0.178	0.093
Clusters (n)	105	105	105	105	105

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.14: Electric vehicle & wind turbine innovation performance model estimation results 2008-2011.

Indicators	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size	4.5 (2.5)*				4.8 (2.9)*
Adjacency	-1.8 (1.7)				-1.2 (2.0)
Regional specialization	0.32 (0.21)				0.43 (0.18)**
Corporate research	-0.31 (1.4)				-0.41 (1.2)
National innovation system		1.4 (0.47)***			1.9 (0.59)***
Knowledge inflow			-0.13 (0.080)		-0.19 (0.094)**
Knowledge outflow			-0.26 (0.17)		-0.39 (0.15)**
Network reach			0.19 (0.14)		
Network density			0.27 (0.15)*		0.40 (0.14)***
Past innovation performance				0.16 (0.10)	
Constant	8.0 (6.6)	-1.2 (0.74)	1.1 (0.18)***	0.72 (0.23)***	7.0 (9.0)
Adjusted R^2	-0.003	0.056	0.020	0.034	0.141
Clusters (n)	62	62	62	62	62

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.15: Sustainable energy cluster innovation performance model diagnostics ($n = 167$).

Model	VIF	Shapiro-Wilk W	Shapiro-Wilk p	Breusch-Pagan BP	Breusch-Pagan p
Threshold values	< 2		< 0.10		< 0.10
Control	0	0.52	0	2.09	0.15
Agglomeration	1.1	0.98	0.01	8.15	0.15
National	0	0.98	0.02	6.81	0.03
Knowledge networks	1.43	0.97	0	10.52	0.06
Path dependence	0	0.98	0.06	3.69	0.16
Agglomeration & networks	1.36	0.97	0	11.92	0.22

B.4 Reference High Technology Clusters

Table B.16: Reference high technology cluster indicator correlation matrix ($n = 1190$).

	IVP	PAT	ADJ	SPE	CRP	NSQ	MNC	LAB	NET_S	NET_W	IVP_P
IVP		0.11***	-0.04	0.38***	0.13***	-0.03	0.05*	0.09***	-0.03	0.00	0.75***
PAT	0.11***		0.04	0.23***	0.06**	0.05*	0.00	-0.10***	0.40***	-0.16***	0.08***
ADJ	-0.04	0.04		0.14***	0.06**	0.08***	0.06**	0.20***	0.10***	0.06**	-0.07**
SPE	0.38***	0.23***	0.14***		0.09***	-0.21***	0.00	0.24***	0.21***	0.09***	0.26***
CRP	0.13***	0.06**	0.06**	0.09***		-0.06**	0.09***	0.06**	0.05*	-0.09***	0.09***
NSQ	-0.03	0.05*	0.08***	-0.21***	-0.06**		0.14***	0.02	0.08***	0.01	0.00
MNC	0.05*	0.00	0.06**	0.00	0.09***	0.14***		-0.18***	0.13***	0.16***	0.05*
LAB	0.09***	-0.10***	0.20***	0.24***	0.06**	0.02	-0.18***		-0.11***	0.48***	0.06**
NET_S	-0.03	0.40***	0.10***	0.21***	0.05*	0.08***	0.13***	-0.11***		-0.03	-0.12***
NET_W	0.00	-0.16***	0.06**	0.09***	-0.09***	0.01	0.16***	0.48***	-0.03		0.03
IVP_P	0.75***	0.08***	-0.07**	0.26***	0.09***	0.00	0.05*	0.06**	-0.12***	0.03	

Table B.17: High technology aggregate cluster innovation performance model estimation results 2008-2011.

Indicators	**Control**	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size		0.65 (0.10)***				0.62 (0.12)***
Adjacency		-0.28 (0.052)***				-0.35 (0.053)***
Regional specialization		0.43 (0.038)***				0.43 (0.040)***
Corporate research		0.37 (0.079)***				0.38 (0.081)***
National innovation system			0.074 (0.18)			0.56 (0.16)***
Knowledge inflow				0.11 (0.037)***		0.014 (0.035)
Knowledge outflow				0.39 (0.073)***		0.17 (0.079)**
Network reach				-0.11 (0.029)***		
Network density				-0.26 (0.063)***		-0.062 (0.064)
Past innovation performance					0.70 (0.022)***	
Knowledge base (dummy)	0.33 (0.17)**	-0.12 (0.048)**	0.035 (0.046)	0.13 (0.049)***	-0.031 (0.031)	-0.11 (0.049)**
Constant	1.8 (0.088)***	1.9 (0.26)***	0.19 (0.29)	0.39 (0.072)***	-0.12 (0.024)***	0.77 (0.43)*
Adjusted R^2	0.003	0.183	-0.001	0.040	0.560	0.196
Adjusted $/DeltaR^2$		0.180	-0.004	0.038	0.558	0.194
Clusters (n)	1180	1180	1180	1180	1180	1180

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.18: High technology scientific knowledge base cluster innovation performance model estimation results 2008-2011.

Indicators	**Control**	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size		0.64 (0.12)***				0.67 (0.14)***
Adjacency		-0.24 (0.063)***				-0.32 (0.063)***
Regional specialization		0.56 (0.049)***				0.55 (0.053)***
Corporate research		0.29 (0.089)***				0.28 (0.092)***
National innovation system			-0.25 (0.26)			0.40 (0.24)*
Knowledge inflow				0.11 (0.062)*		0.049 (0.053)
Knowledge outflow				0.62 (0.10)***		0.28 (0.11)**
Network reach				0.11 (0.047)**		
Network density				-0.33 (0.090)***		-0.048 (0.097)
Past innovation performance					0.78 (0.026)***	
Constant	9.3 (1.5)***	1.9 (0.29)***	0.76 (0.43)*	0.20 (0.12)*	-0.22 (0.023)***	1.3 (0.55)**
Adjusted R^2	0.035	0.319	0.000	0.077	0.674	0.334
Clusters (n)	586	586	586	586	586	586

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.19: High technology engineering & design knowledge base cluster innovation performance model estimation results 2008-2011.

Indicators	**Control**	**Agglomeration**	**National**	**Knowledge Networks**	**Path Dependence**	**Agglomeration & Network**
Cluster size		0.12 (0.17)				-0.042 (0.22)
Adjacency		-0.33 (0.080)***				-0.37 (0.084)***
Regional specialization		0.20 (0.052)***				0.22 (0.055)***
Corporate research		0.47 (0.20)**				0.48 (0.20)**
National innovation system			0.47 (0.22)**			0.72 (0.22)***
Knowledge inflow				0.094 (0.041)**		-0.012 (0.044)
Knowledge outflow				0.13 (0.093)		0.090 (0.11)
Network reach				-0.25 (0.032)***		
Network density				-0.068 (0.082)		-0.10 (0.088)
Past innovation performance					0.59 (0.034)***	
Constant	-0.29 (1.0)	0.19 (0.42)	-0.46 (0.35)	0.62 (0.081)***	-0.053 (0.027)**	-1.5 (0.72)**
Adjusted R^2	0.000	0.036	0.006	0.127	0.423	0.050
Clusters (n)	594	594	594	594	594	594

Note: Beta-coefficient values and standard error in parentheses. *, ** and *** marks statistical significance at the 90%, 95% and 99%-level, respectively.

Table B.20: High technology aggregate model diagnostics (n = 1180).

Model	VIF	Shapiro-Wilk W	Shapiro-Wilk p	Breusch-Pagan BP	Breusch-Pagan p
Threshold values	< 2		< 0.10		< 0.10
Control	0	0.48	0	2.22	0.14
Agglomeration	1.21	0.98	0	15.21	0.01
National	0	0.98	0	18.95	0
Knowledge networks	1.43	0.98	0	60.28	0
Path dependence	0	0.98	0	39.01	0
Agglomeration & networks	1.47	0.97	0	21.64	0.01

Appendix C

Cluster Spatial Distribution, Agglomeration and Knowledge Networks

C.1 Robustness Analysis for Minimum Cluster Size

Descriptive statistics of the technology cluster spatial distribution, agglomeration and knowledge network patterns are partly influenced by the setting of a minimum cluster size. A ten inventor minimum is used in this study, however the effects of a higher 20 inventor limit are also explored. Because the two limits produce similar results, the ten inventor limit is used in the study in order to maximize the total number of clusters (n) available for inclusion in the analysis. See table C.1 and table C.2.

Table C.1: Robustness check of health technology cluster inventor minimum (10 and 20 inventors) with cluster, agglomeration and knowledge network statistics 2008-2011.

Indicators	**10-Inventor Cluster**	**20-Inventor Cluster**
Clusters & Agglomeration		
Total patents	72,051	72051
- Patents in North America	38,405 (53%)	38,405 (53%)
- Patents in Europe	16,062 (22%)	16,062 (22%)
- Patents in Asia	16,176 (22%)	16,176 (22%)
- Patents in Rest of World	1,408 (2%)	1,408 (2%)
Total Clusters	219	211
- Clusters in North America	133 (61%)	128 (61%)
- Clusters in Europe	47 (21%)	44 (21%)
- Clusters in Asia	32 (15%)	32 (15%)
- Clusters in Rest of World	7 (3%)	7 (3%)
Clustered patents	30,332 (42%)	30,277 (42%)
Patents per cluster, average	138.5	143.5
Cluster size Gini coefficient	0.67	0.67
Corporate patenting share	73.4	73
Knowledge Networks (cluster average)		
Co-invention links per inventor	0.51	0.5
Network reach per cluster	35.2	36.2
Network density per cluster	109.2	112.9
Knowledge inflow per inventor	0.59	0.6
Knowledge outflow per inventor	0.64	0.62
Median co-invention distance (km)	50	50

Table C.2: Robustness check of sustainable energy cluster inventor minimum (10 and 20 inventors) with cluster, agglomeration and knowledge network statistics 2008-2011.

Indicators	**10-Inventor Cluster**	**20-Inventor Cluster**
Clusters & Agglomeration		
Total patents	24,171	24171
- Patents in North America	9,086 (38%)	9,086 (38%)
- Patents in Europe	4,742 (20%)	4,742 (20%)
- Patents in Asia	10,083 (42%)	10,083 (42%)
- Patents in Rest of World	260 (1%)	260 (1%)
Total Clusters	167	120
- Clusters in North America	74 (44%)	46 (38%)
- Clusters in Europe	29 (17%)	20 (17%)
- Clusters in Asia	62 (37%)	52 (43%)
- Clusters in Rest of World	2 (1%)	2 (2%)
Clustered patents	11,248 (47%)	10,770 (45%)
Patents per cluster, average	67.4	89.7
Cluster size Gini coefficient	0.7	0.66
Corporate patenting share	85.8	87.2
Knowledge Networks (cluster average)		
Co-invention links per inventor	0.32	0.29
Network reach per cluster	7	8.3
Network density per cluster	15	18.8
Knowledge inflow per inventor	0.6	0.65
Knowledge outflow per inventor	0.52	0.49
Median co-invention distance (km)	47	47

C.2 Health Technology Clusters

Table C.3: Health technology cluster, agglomeration and knowledge network statistics by sub-sector 2008-2011.

Indicators	**Medical Life Sciences**	**Medical Devices**
Clusters & Agglomeration		
Total patents	27,080	44,971
- Patents in North America	14,776 (55%)	23,629 (53%)
- Patents in Europe	6,675 (25%)	9,387 (21%)
- Patents in Asia	4,837 (18%)	11,339 (25%)
- Patents in Rest of World	792 (3%)	617 (1%)
Total Clusters	146	73
- Clusters in North America	72 (49%)	61 (84%)
- Clusters in Europe	44 (30%)	3 (4%)
- Clusters in Asia	23 (16%)	9 (12%)
- Clusters in Rest of World	7 (5%)	0 (0%)
Clustered patents	19,408 (72%)	10,923 (24%)
Patents per cluster, average	132.9	149.6
Cluster size Gini coefficient	0.67	0.68
Corporate patenting share	65.9%	88.3%
Knowledge Networks (cluster average)		
Co-invention links per inventor	0.59	0.35
Network reach (unique links per cluster)	35.6	34.4
Network density (total links per cluster)	101.7	124.3
Knowledge inflow (links per inventor)	0.55	0.66
Knowledge outflow (links per inventor)	0.57	0.79
Median co-invention distance (km)	52	48

Table C.4: Countries with 10 largest health technology sectors 2000-2011 (share of world health technology patents).

Rank	2000-2003	2004-2007	2008-2011
1	United States (51.2%)	United States (50.6%)	United States (50.7%)
2	Japan (13.2%)	Japan (14.2%)	Japan (12.9%)
3	Germany (7.6%)	Germany (7.7%)	Germany (7.1%)
4	United Kingdom (3.6%)	United Kingdom (2.8%)	France (2.8%)
5	France (3.4%)	Canada (2.8%)	United Kingdom (2.7%)
6	Canada (3.2%)	France (2.7%)	South Korea (2.7%)
7	Israel (2.1%)	Israel (2.4%)	Canada (2.5%)
8	Switzerland (1.6%)	South Korea (2.1%)	Israel (2.2%)
9	South Korea (1.4%)	Switzerland (1.7%)	Taiwan (1.9%)
10	Sweden (1.4%)	Taiwan (1.4%)	Switzerland (1.7%)

Table C.5: Cities with 10 largest health technology clusters by sub-sector 2008-2011 (share of world health technology patents).

Rank	Medical Life Sciences	Medical Devices
1	San Francisco, US (7%)	Tokyo, JP (3%)
2	New York, US (6%)	Los Angeles, US (2%)
3	Boston, US (5%)	San Jose, US (2%)
4	Tokyo, JP (4%)	Boston, US (2%)
5	San Diego, US (4%)	Seattle, US (1%)
6	Washington, US (3%)	New York, US (1%)
7	Los Angeles, US (2%)	Seoul, KR (1%)
8	Osaka, JP (2%)	Tel Aviv-Yafo, IL (1%)
9	Kobenhavn, DK (2%)	San Diego, US (1%)
10	Seoul, KR (2%)	Taipei, TW (1%)

C.3 Sustainable Energy Clusters

Table C.6: Sustainable energy cluster, agglomeration and knowledge network statistics by sub-sector 2008-2011.

Indicator	**Biofuels**	**Electric Vehicles***	**Electricity Storage**	**Fuel Cells**	**Hydrogen Technology**	**Photovoltaics**	**Wind Turbines***
Clusters & Agglomeration							
Total patents	1,953	6,070	3,391	2,041	1,103	6,360	3,253
- Patents in North America	1,215 (62%)	1,783 (29%)	1,020 (30%)	655 (32%)	491 (45%)	2,716 (43%)	1,206 (37%)
- Patents in Europe	449 (23%)	834 (14%)	473 (14%)	325 (16%)	253 (23%)	1,080 (17%)	1,329 (41%)
- Patents in Asia	218 (11%)	3,425 (56%)	1,865 (55%)	1,045 (51%)	341 (31%)	2,514 (40%)	675 (21%)
- Patents in Rest of World	71 (4%)	27 (0%)	34 (1%)	16 (1%)	18 (2%)	51 (1%)	43 (1%)
Total Clusters	33	35	17	18	16	21	27
- Clusters in North America	23 (70%)	14 (40%)	8 (47%)	7 (39%)	7 (44%)	9 (43%)	6 (22%)
- Clusters in Europe	3 (9%)	7 (20%)	2 (12%)	2 (11%)	1 (6%)	2 (10%)	12 (44%)
- Clusters in Asia	6 (18%)	14 (40%)	7 (41%)	9 (50%)	8 (50%)	10 (48%)	8 (30%)
- Clusters in Rest of World	1 (3%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (4%)
Clustered patents	711 (36%)	4,361 (72%)	905 (27%)	1,064 (52%)	312 (28%)	2,805 (44%)	1,090 (33%)
Patents per cluster, average	21.6	124.6	53.2	59.1	19.5	133.6	40.4
Cluster size Gini coefficient	0.51	0.76	0.61	0.63	0.45	0.67	0.49
Corporate patenting share	71.9%	95%	83.2%	82.1%	70.5%	91.6%	99.3%
Knowledge Networks (cluster average)							
Co-invention links per inventor	0.43	0.24	0.22	0.18	0.19	0.26	0.54
Network reach (unique links per cluster)	7.4	7.3	5.5	5.2	3.6	9.1	8.4
Network density (total links per cluster)	14.7	16.1	9.5	9.1	5.5	24.5	19.7
Knowledge inflow (links per inventor)	0.55	0.54	0.91	0.32	0.26	0.65	0.87
Knowledge outflow (links per inventor)	0.43	0.48	0.51	0.53	0.41	0.54	0.72
Median co-invention distance (km)	72	38	52	51	73	50	92

Table C.7: Countries with 10 largest sustainable energy sectors 2000-2011 (share of world sustainable energy patents).

Rank	2000-2003	2004-2007	2008-2011
1	Japan (38.3%)	Japan (34.1%)	United States (35.8%)
2	United States (31%)	United States (32.4%)	Japan (28.5%)
3	Germany (10%)	Germany (8.7%)	Germany (7.7%)
4	Canada (3.1%)	South Korea (5.6%)	South Korea (6.9%)
5	South Korea (2.2%)	Canada (2.8%)	France (2.6%)
6	United Kingdom (2.1%)	France (2.4%)	Taiwan (2.4%)
7	France (2.1%)	United Kingdom (2.1%)	Denmark (2.2%)
8	Taiwan (1.5%)	Taiwan (2%)	China (2%)
9	Denmark (1.2%)	Denmark (1.4%)	United Kingdom (1.9%)
10	Australia (1.1%)	Italy (1%)	Canada (1.7%)

Table C.8: Cities with the slowest-growing sustainable energy clusters 2000-2011 (absolute growth).

Rank	City	*/Delta* Patents	Rate
27	Hartford, US	30	263%
28	Fremont, US	28	119%
29	Munich, DE	23	34%
30	Taichung, TW	23	125%
31	Vancouver, CA	19	100%
32	Utsunomiya, JP	17	45%
33	Chiba, JP	11	34%
34	Erie, US	4	25%
35	Shizuoka, JP	1	2%
36	Carmel, US	0	-2%

Table C.9: Cities with the 10 largest sustainable energy innovation clusters by sub-sector 2008-2011 (part 1).

Rank	Biofuels	Electric Vehicles*	Electricity Storage	Fuel Cells
1	San Francisco, US (6%)	Nagoya, JP (20%)	Tokyo, JP (7%)	Tokyo, JP (13%)
2	Wilmington, US (4%)	Tokyo, JP (14%)	Nagoya, JP (5%)	Seoul, KR (9%)
3	Boston, US (3%)	Detroit, US (8%)	San Francisco, US (4%)	Nagoya, JP (8%)
4	Kobenhavn, DK (3%)	Osaka, JP (5%)	Daejeon, KR (3%)	Osaka, JP (6%)
5	Aurora, US (2%)	Seoul, KR (4%)	Seoul, KR (2%)	Rochester, US (3%)
6	Pasadena, US (2%)	Mito, JP (3%)	Kyoto, JP (2%)	Fremont, US (2%)
7	San Diego, US (2%)	San Francisco, US (3%)	Beijing, CN (1%)	Hartford, US (2%)
8	Tokyo, JP (1%)	Stuttgart, DE (2%)	Boston, US (1%)	Vancouver, CA (1%)
9	The Hague, NL (1%)	Los Angeles, US (2%)	San Diego, US (1%)	Daejeon, KR (1%)
10	Sioux Falls, US (1%)	Daejeon, KR (1%)	Chiba, JP (1%)	Utsunomiya, JP (1%)

Table C.10: Cities with the 10 largest sustainable energy innovation clusters by sub-sector 2008-2011 (part 2).

Rank	Hydrogen Technology	Photovoltaics	Wind Turbines*
1	Tokyo, JP (5%)	San Francisco, US (11%)	Tokyo, JP (5%)
2	Nagoya, JP (5%)	Tokyo, JP (9%)	Aarhus, DK (4%)
3	Osaka, JP (3%)	Seoul, KR (7%)	Greenville, US (3%)
4	Seoul, KR (3%)	Osaka, JP (5%)	Albany, US (3%)
5	Grenoble, FR (2%)	Taipei, TW (2%)	Nagasaki, JP (2%)
6	Princeton, US (1%)	Boston, US (2%)	Singapore, SG (2%)
7	Ann Arbor, US (1%)	Hsinchu, TW (2%)	Vejle, DK (2%)
8	Utsunomiya, JP (1%)	Daejeon, KR (1%)	Munich, DE (2%)
9	Vancouver, CA (1%)	Ossining, US (1%)	Pamplona, ES (1%)
10	Hsinchu, TW (1%)	Indio, US (1%)	Berlin, DE (1%)

C.4 Reference High Technology Clusters

Table C.11: Comparison of all cluster, agglomeration and knowledge network statistics, 2008-2011 period.

Indicators	**Health Technology**	**Sustainable Energy**	**High Technology**
Total patents	72,051	24,171	743,466
- Patents in North America	38,405 (53%)	9,086 (38%)	337,869 (45%)
- Patents in Europe	16,062 (22%)	4,742 (20%)	132,658 (18%)
- Patents in Asia	16,176 (22%)	10,083 (42%)	263,192 (35%)
- Patents in Rest of World	1,408 (2%)	260 (1%)	9,747 (1%)
Total Clusters	219	167	1,192
- Clusters in North America	133 (61%)	74 (44%)	615 (52%)
- Clusters in Europe	47 (21%)	29 (17%)	304 (26%)
- Clusters in Asia	32 (15%)	62 (37%)	223 (19%)
- Clusters in Rest of World	7 (3%)	2 (1%)	50 (4%)
Clustered patents	30,332 (42%)	11,248 (47%)	533,184 (72%)
Patents per cluster, average	138.5	67.4	447.3
Cluster size Gini coefficient	0.67	0.7	0.84
Corporate patenting share	73.4%	85.8%	88.6%
Co-invention links per inventor	0.51	0.32	0.36
Network reach (unique links per cluster)	35.2	7	57.2
Network density (total links per cluster)	109.2	15	274.8
Knowledge inflow (links per inventor)	0.59	0.6	0.64
Knowledge outflow (links per inventor)	0.64	0.52	0.69
Median co-invention distance (km)	50	47	49

Table C.12: Cities with 10 largest clusters from different sectors (share of world patent output), 2008-2011 period.

Rank	Health Technology	Sustainable Energy	High Technology
1	Tokyo, JP (4%)	Tokyo, JP (9%)	Tokyo, JP (13%)
2	New York, US (3%)	Nagoya, JP (7%)	San Francisco, US (6%)
3	Boston, US (3%)	San Francisco, US (5%)	Seoul, KR (5%)
4	San Francisco, US (2%)	Seoul, KR (4%)	New York, US (3%)
5	Los Angeles, US (2%)	Osaka, JP (3%)	Osaka, JP (3%)
6	San Diego, US (2%)	Detroit, US (2%)	Taipei, TW (2%)
7	Washington, US (1%)	Daejeon, KR (1%)	Boston, US (2%)
8	San Jose, US (1%)	Boston, US (1%)	Los Angeles, US (2%)
9	Seattle, US (1%)	Mito, JP (1%)	Seattle, US (2%)
10	Seoul, KR (1%)	Stuttgart, DE (1%)	San Diego, US (2%)

Appendix D

Innovation Actors

D.1 Health Technology Clusters

The top 10 innovation actors are shown in table D.1 and are derived from raw patent assignee information. Raw assignee information lacks corrections for differences in spelling, subsidiaries from the same corporate entity or changes in assignee names. Because the focus of this analysis is on technology clusters and not on assignees, the assignee information presented here is for illustrative purposes only.

The innovation actors are presented together with a two-letter country code of the country where the actors are registered. Two-letter ISO 3166-1 alpha-2 country codes are used, which are part of the ISO 3166 standard published by the International Organization for Standardization (ISO), to represent countries and dependent territories. These are the most widely used of the country codes published by ISO (the others being alpha-3 and numeric) and are widely used by international organizations, including the United Nations.

Table D.1: Health technology innovation actors by sub-sector, 2008-2011.

Description	Medical Life Sciences	Medical Devices
Universities (%)	21	5
Industry (%)	76	94
Government (%)	2	1
Top 10 Assignees	Genentech, Inc. (US), The Regents of the University of California (US), Monsanto Technology LLC (US), Pioneer Hi-Bred International, Inc. (US), The United States of America as represented by the Department of Health and Human Services (US), Merck & Co., Inc. (US), ISIS Pharmaceuticals, Inc. (US), Eli Lilly and Company (US), Human Genome Sciences, Inc. (US), Amgen Inc. (US)	Covidien LP (US), Siemens Aktiengesellschaft (DE), GENERAL ELECTRIC COMPANY (US), Ethicon Endo-Surgery, Inc. (US), TYCO Healthcare Group LP (US), Koninklijke Philips N.V. (NL), Boston Scientific Scimed, Inc. (US), Canon Kabushiki Kaisha (JP), Olympus Medical Systems Corp. (JP), FUJIFILM Corporation (JP)

Table D.2: Health technology patents, clusters and share by sub-sector, 2008-2011.

Description	Medical Life Sciences	Medical Devices
Patents in clusters (count)	17,561	10,110
Patents per sector (%)	63	37
Clusters (count)	146	73
Clusters per sector (%)	67	33

D.2 Sustainable Energy Clusters

The top 10 innovation actors are shown in table D.3 and are derived from raw patent assignee information (see appendix D.2 for further details).

Note: in table D.3 * indicates sub-sector with engineering knowledge base.

Table D.3: Sustainable energy innovation actors by sub-sector, 2008-2011.

Sector	**Universities (%)**	**Industry (%)**	**Government (%)**	**Top 10 Assignees**
Biofuels	12	87	1	Novozymes A/S (DK), Danisco US Inc. (US), Heliae Development, LLC (US), Coskata, Inc. (US), E I du Pont de Nemours and Company (US), Butamax(TM) Advanced Biofuels LLC (US), Poet Research, Inc. (US), Butamax Advanced Biofuels LLC (US), The Regents of the University of California (US), Novozymes, Inc. (US)
Electric Vehicles*	2	98	0	TOYOTA JIDOSHA KABUSHIKI KAISHA (JP), Ford Global Technologies, LLC (US), GM Global Technology Operations LLC (US), Honda Motor Co., Ltd. (JP), Nissan Motor Co., Ltd. (JP), General Electric Company (US), ROBERT BOSCH GMBH (DE), DENSO CORPORATION (JP), Hitachi, Ltd. (JP), Honda Giken Kogyo Kabushiki Kaisha (JP)
Electricity Storage	6	93	1	Samsung SDI Co., Ltd. (KR), Toyota Jidosha Kabushiki Kaisha (JP), Sony Corporation (JP), LG Chem, Ltd. (KR), Robert Bosch GmbH (DE), Panasonic Corporation (JP), GM Global Technology Operations LLC (US), Sanyo Electric Co., Ltd. (JP), Semiconductor Energy Laboratory Co., Ltd. (JP), Corning Incorporated (US)
Fuel Cells	10	89	2	Toyota Jidosha Kabushiki Kaisha (JP), GM Global Technology Operations LLC (US), Samsung SDI Co., Ltd. (KR), Honda Motor Co., Ltd. (JP), Sony Corporation (JP), Bloom Energy Corporation (US), Hyundai Motor Company (KR), PANASONIC CORPORATION (JP), Kabushiki Kaisha Toshiba (JP), Audi AG (DE)
Hydrogen Technology	12	85	3	Honda Motor Co., Ltd. (JP), GM Global Technology Operations LLC (US), Toyota Jidosha Kabushiki Kaisha (JP), Societe BIC (FR), Samsung Electro-Mechanics Co., Ltd. (KR), The Trustees of Princeton University (US), Honeywell International Inc. (US), Panasonic Corporation (JP), Young Green Energy Co. (TW), Toyota Motor Engineering & Manufacturing North America, Inc. (US)
Photovoltaics	5	95	1	International Business Machines Corporation (US), LG Electronics Inc. (KR), E I Du Pont de Nemours and Company (US), Sharp Kabushiki Kaisha (JP), Applied Materials, Inc. (US), Mitsubishi Electric Corporation (JP), Sanyo Electric Co., Ltd. (JP), SunPower Corporation (US), Industrial Technology Research Institute (TW), The Boeing Company (US)
Wind Turbines*	2	98	0	General Electric Company (US), Vestas Wind Systems A/S (DK), SIEMENS AKTIENGESELLSCHAFT (DE), Mitsubishi Heavy Industries, Ltd. (JP), Gamesa Innovation & Technology, S.L. (ES), Nordex Energy GmbH (DE), SENVION SE (DE), LM Glasfiber A/S (DK), Hitachi, Ltd. (JP), (US)

Table D.4: Sustainable energy patents, clusters and share by sub-sector, 2008-2011.

Sector	**Patents (count)**	**Patents per sector (%)**	**Clusters (count)**	**Clusters per sector (%)**
Biofuels	668	9	33	20
Electric Vehicles*	3,599	25	35	21
Electricity Storage	750	14	17	10
Fuel Cells	868	8	18	11
Hydrogen Technology	255	5	16	10
Photovoltaics	2,411	27	21	13
Wind Turbines*	910	13	27	16

Note: * indicates sub-sector with engineering knowledge base.

Summary

Motivation

The sustainability technology sectors, encompassing health and sustainable energy technology, play a critically important role in addressing global challenges such as climate change and ageing populations, which require a transition to a low or zero-carbon energy system, and sustainable and affordable healthcare. While these problems cannot be resolved by technological solutions alone, technology plays an important part in addressing them. Innovation, climate change, public health and the need for sustainable industrialization and economic growth are also part of the Sustainable Development Goals of the United Nations, further highlighting their global importance. Another motivation for the study, specifically from a European perspective, is a concern over the long-term economic competitiveness of Europe, which appears to be lagging behind the United States and certain Asian countries. This concern is a driver of the European Union's current science and technology policy, including its multi-billion euro Horizon Europe initiative and Smart Specialization strategies for European regions.

Research Question and Knowledge Gaps

The main research question addressed in this dissertation is: *How are the dynamic spatial distribution and innovation performance patterns of sustainability technology clusters influenced by cluster characteristics, such as agglomeration and knowledge networks, and sectoral differences?* Although there is an extensive literature on evolutionary economic geography, innovation systems, and global innovation diffusion, these theories often lack specificity with regard to particular technology sectors. Relatively little is known about the spatial distribution, cluster characteristics, and cluster innovation performance in the sustainability technology sectors. There are three main knowledge gaps: (i) the global spatial distribution and knowledge networks of technology clusters and their changes over time, (ii) the association between cluster innovation performance and various cluster characteristics, and (iii) the extent to which the aforementioned factors are influenced by socio-technological transitions and other sectoral differences. These knowledge gaps are addressed with a novel empirical approach to cluster identification, the measurement of cluster characteristics and the modeling of innovation performance.

Concepts and Theory

Innovation performance is one of the core concepts defined in chapter 2. Concisely defined, innovation performance is the ability of an organization to generate new knowledge and apply it

in an economically useful way. Innovation performance is influenced by both internal and external factors, which act at multiple spatial scales. Among these, technology clusters are one of the most important spatial scales, with important interactions between organizations (such as between firms and universities) taking place there. At a higher spatial scale, the national innovation system, which includes regulations, funding, and national institutions and policies, also influences innovation performance, although increasing globalization has reduced the influence of national governments to a certain extent. At a global scale, inter-cluster knowledge networks facilitate learning, collaboration, and other knowledge relationships between different clusters, although these relationships are sometimes unequal, resulting in "reverse" knowledge flows. Also notable is path dependence: because knowledge, experience, skills and relationships accumulate over time, already successful technology clusters tend to maintain high innovation performance.

There is considerable sectoral variation in cluster characteristics, including in the strength and direction of association (positive or negative) between cluster characteristics and innovation performance. These differences can be attributed to the sectoral knowledge base and development phase: in sectors with an engineering and design knowledge base, spatial proximity is seen as more important because it facilitates the exchange of tacit knowledge. In sectors with a scientific knowledge base, knowledge transfers over long distances appear to be facilitated by the prevalence of codified knowledge. Sectors in an emerging phase tend to have lower path dependence, sparser knowledge networks, and high levels of new cluster creation. Over time, as a sector and technology clusters mature, agglomeration and the size of knowledge networks expand. National policies can play a role in supporting the creation and growth of technology clusters. To gain a clearer understanding of the cluster characteristics and innovation performance of sustainability technology clusters, 12 hypotheses are proposed, which can be divided into six groups: (i) Changes in the global spatial distribution of technology clusters (hypothesis 1), (ii) sectoral differences (hypotheses 2 & 12), (iii) different aspects of agglomeration at the cluster and regional scale (hypotheses 3-5), (iv) national innovation system (hypothesis 6), (v) inter-cluster knowledge flows and knowledge networks (hypotheses 7-10) and (vi) path dependence (hypotheses 11 and 12).

Data and Methodology

A novel cluster innovation performance model, including model indicators, and cluster identification methodology are the focus of chapters 3 and 4. The cluster innovation performance model is an adaptation of earlier knowledge production functions, in which the association between cluster characteristics and innovation performance is explored. In the present study, the dependent variable is a composite indicator of patent citations divided by the number of inventors. Citations are a measure of patent quantity *and* quality (Hall, Jaffe, and Trajtenberg 2005) and the inventors are a proxy for knowledge inputs. This approach successfully models the cluster characteristics associated with cluster innovation outperformance across diverse high technology sectors, including the sustainability technology sectors. The independent variables of the model describe agglomeration, the national innovation system, inter-cluster knowledge networks, and path dependence.

Technology clusters are identified using a novel patent "heat map" methodology which identifies clusters based on the real location of innovation activity and provides a more accurate picture of the spatial distribution and characteristics of clusters as compared to using pre-defined administrative boundaries. The methodology differs from earlier "organic" cluster studies (Catini et al. 2015; Alcácer and Zhao 2016; Bergquist, Fink, and Raffo 2017) in three main aspects: (i) it uses a single data source, namely the patent grant database of the United States Patent & Trademark Office, USPTO, to ensure a uniform standard of patent evaluation, (ii) it uses a home bias correction to compensate for differences in patenting and citation frequency between the United States and other countries, and (iii) it uses a Kernel Density Estimation method (Rosenblatt 1956; Parzen 1962) to calculate a patent "heat map" from which technology clusters are identified. Parameters are optimized to detect small clusters and avoid detecting unrealistically large clusters. The methodology enables a more precise identification of technology clusters and measurement of cluster indicators, and the construction of a unique global database of technology cluster metrics.

Results: Global Spatial Distribution & Patterns

The health technology sector is analyzed in chapter 5 and consists of two technological sub-sectors: medical devices and medical life sciences. The sustainable energy technology sector is analyzed in chapter 6 and consists of seven technological sub-sectors: biofuels, electric vehicles, electricity storage, fuel cells, hydrogen technology, photovoltaics and wind turbines. The sub-sectors are among the most innovative within their respective sectors and include both sub-sectors with an engineering and design knowledge base (medical devices, electric vehicles and wind turbines) and with a scientific knowledge base (medical life sciences, hydrogen technology, photovoltaics and others). Chapters 5 and 6 provide a descriptive analysis of the spatial distribution, agglomeration, and knowledge networks of the sectors, and a quantitative analysis of the association between innovation performance and cluster characteristics. A comparative perspective is presented in chapter 7, together with a discussion of relevant policy applications.

The largest technology clusters (by patent output) are usually located in large "global" cities such as San Francisco, Tokyo, New York, and Los Angeles, although the spatial pattern of sustainable energy technology is different, as around half of the 10 largest clusters are found in smaller lower-tier cities such as Daejeon, Detroit, Nagoya, and Stuttgart. In sub-sectors such as biofuels and wind turbines, the largest technology clusters are found in small cities, such as Aarhus (Denmark), Aurora (Colorado, United States), and Pamplona (Spain). This confirms prior observations that niche high technology clusters can develop in relatively peripheral locations. Viewed globally, health technology innovation is concentrated in North America, whereas sustainable energy technology is concentrated in Asia (Japan, South Korea, and Taiwan). Europe is lagging behind, although it plays a leading role in some sub-sectors such as wind turbines.

The sustainable energy technology sector is growing rapidly, with 100 new clusters emerging during the study periods. New clusters are being created in many different countries, including in innovation leaders such as the United States and in countries with modest innovation capabilities, such as Spain and India. In absolute terms, most clusters have been created in North America. During the study period the average cluster size, the share of patents found in clusters (clustering rate) and inter-cluster knowledge network density all increased. In contrast, the number of health technology clusters, and their agglomeration and knowledge network characteristics, remained mostly unchanged.

Viewed from a national perspective, sustainable energy research is increasing in China, Denmark, France, South Korea, Taiwan, and the United States, but declining in Canada, Germany, Japan, and the United Kingdom (in relative terms). Health technology research shows a different pattern, with growth in China, South Korea, and Taiwan, while the share of the United States and Japan is stable, and European countries' share is declining (in relative terms). This suggests that a "global shift" is taking place from Europe to Asia in the health technology sector, while the direction of "global shifts" is more complex for sustainable energy technology.

Results: Cluster Innovation Performance

The cluster innovation performance model results provide insights into the cluster characteristics associated with innovation performance, specifically agglomeration, the national innovation system, knowledge networks, and path dependence. With regards to agglomeration, the results confirms a positive association between economies of scale (cluster size) and cluster absorptive capacity (corporate research). However, agglomeration effects differ when a cluster is located relatively close to other large clusters (< 200 km, adjacency effect), a situation that usually occurs if a cluster is part of a larger conurbation. For instance, the Utsunomiya, Mito and Chiba sustainable energy clusters are all located within 200 km of Tokyo, and can be considered to be part of "Greater Tokyo." While spatial proximity can have benefits, such as access to a deeper talent pool and specialized service providers, increased competition for talent and resources appear to outweigh these benefits at the scale of large conurbations. It should be noted that the negative association with adjacency is not found in sustainable energy technology clusters, presumably due to their smaller size and emerging development phase. The sustainable energy technology sector is also unique in the sense that the national innovation system has a statistically significant influence on cluster innovation performance, which is not the case in other sectors.

Access to a large number of different clusters (network reach) and outbound knowledge flows are positively associated with cluster innovation performance in the health technology sector. Knowledge outflow is facilitated by multinational corporations, and their positive relationship with innovation performance supports the observation that multinational corporations often establish themselves in already-successful clusters (Awate, Larsen, and Mudambi 2015; Østergaard and Park 2015). Knowledge outflow is not statistically significant in the emerging sustainable energy technology sector. Path dependence positively influences cluster innovation performance in all sectors, although its association is weaker in the emerging sustainable energy sector. The empirical findings show clear differences between the sustainable energy technology and health technology sectors.

Research Contributions

The research contributions are described in chapter 8 and apply to four main areas: methodology, novel empirical results, theory, and policy. The methodological contribution involves the identification of technology clusters from patent data and the characterization of these clusters using novel indicators, providing a comprehensive global overview of a sector's technology clusters and inter-cluster knowledge networks. Such data has previously been difficult to obtain and is also the main empirical contribution of this study. The theoretical contributions of the study center on showing the differences between the health technology and sustainable energy technology sectors, differences which cannot be attributed only to their development phase. Although the lower path dependence and lack of negative agglomeration effects of the emerging sustainable energy technology sector are expected, the sector also has a lower influence from corporate research and is influenced more strongly by national institutions and policies (national innovation system). This difference is likely due to the socio-technological transition taking place in the energy system, which involves significant influence from non-corporate actors. The absence of these influences in the health technology sector suggests that socio-technological transitions in healthcare differ markedly from those in sustainable energy technology, which involve profound shifts, not only in technology, but also the business model of the sector. The research findings also suggest that relatively large sustainability technology clusters located in smaller cities enable high innovation performance. Such a situation appears to take advantage of local agglomeration economies while mitigating the diseconomies of scale that occur when clusters are located in large conurbations (adjacency), and could apply to other emerging high technology sectors as well (Steen and Hansen 2018). From a policy perspective, the methodology offers a useful tool for monitoring the creation and growth of technology clusters, their networks, and key innovation actors, on a worldwide scale. The study also shows significant differences between sectors, especially with regards to sustainable energy technology. Policies supporting technology cluster development should therefore be customized depending on the sector's knowledge base, development phase, and socio-technological context.

Conclusion

Research limitations, reflections, and the conclusion are found in chapter 9. The main limitations include the time period selection and the model design which, because of limitations imposed by the patent data, could not measure theoretical concepts related to cluster innovation performance such as entrepreneurship, social capital, or policy incentives. These limitations could be addressed in future research by performing detailed cluster case studies which focus on these areas. Despite these limitations, the research findings shed light on the concept of cluster innovation performance, the nature of global shifts in innovation and differences in socio-technological transitions. In this study innovation performance has been operationalized as an efficiency indicator. However, only around 30-60% of cluster innovation performance can be explained by the model, and it is mainly accounted for by path dependence. Possible reasons for this is that cluster innovation performance depends largely on the performance of specific technological niches, and that the growth of clusters is often driven by other factors such as the strategic business and technological decisions by firms, and various other incentives. Global shifts in the spatial distribution of cluster creation and growth appear closely related to local factors, such as the availability of knowledge resources, investment and supportive policies. Although countries such as China, South Korea, and Taiwan have successfully supported the development and growth of technology clusters, similar policies are also undertaken in other parts of the world, although on a smaller scale and for specific sectors such as sustainable energy.

There also appears to be a large difference between the type of socio-technological transitions taking place in the energy and healthcare system. In the energy sector, the adoption of new sustainable energy technologies requires fundamental changes in the business models of energy generation and distribution. However, in the health technology sector, business models appears to be mostly unchanged. These differences are especially evident from the significance, or lack thereof, of corporate research and the national innovation system. These differences could be further explored by studying other emerging high technology sectors and time periods.

Samenvatting

Motivatie

De duurzaamheidstechnologiesectoren, waaronder gezondheidstechnologie en duurzame energietechnologie, spelen een cruciale rol bij de aanpak van mondiale uitdagingen zoals klimaatverandering en vergrijzing. Hoewel deze problemen niet met technologie alléén kunnen worden opgelost, speelt technologie hier een belangrijke rol bij. Innovatie, klimaatverandering, volksgezondheid en de noodzaak van duurzame industrialisering en economische groei maken ook deel uit van de Sustainable Development Goals van de Verenigde Naties, iets wat hun wereldwijde belang benadrukt. Een andere motivatie voor het onderzoek, vanuit Europees perspectief, is bezorgdheid over het economische concurrentievermogen van Europa. Het continent lijkt achter te blijven bij de Verenigde Staten en bepaalde Aziatische landen, en deze zorg is een drijvende kracht achter het huidige wetenschaps- en technologiebeleid van de Europese Unie, inclusief het miljarden euro kostende Horizon Europe-initiatief en het *Smart Specialisation* strategieën voor Europese regio's.

Onderzoeksvraag en kennislancunes

De belangrijkste onderzoeksvraag die in dit proefschrift aan de orde komt is: *Hoe worden de dynamische ruimtelijke spreidings- en innovatieprestatiepatronen van duurzaamheidstechnologieclusters beïnvloed door clusterkenmerken zoals agglomeratie en kennisnetwerken, en sectorale verschillen?* Hoewel er een uitgebreide literatuur bestaat over evolutionaire economische geografie, innovatiesystemen en wereldwijde innovatiediffusie, ontbreekt het vaak aan specificiteit met betrekking tot individuele technologiesectoren. Er is relatief weinig bekend over de ruimtelijke spreiding, clusterkenmerken en clusterinnovatieprestaties in de duurzaamheidstechnologiesectoren. Er zijn in feite drie belangrijke kennislancunes: (i) de wereldwijde ruimtelijke distributie en kennisnetwerken van technologieclusters en hun veranderingen in de tijd, (ii) het verband tussen clusterinnovatieprestaties en bepaalde clusterkenmerken, en (iii) de mate waarin deze verbanden worden beïnvloed door sociaal-technologische transities en andere sectorale verschillen. Deze kennislacunes worden benaderd met een nieuwe methode voor clusteridentificatie, het meten van clusterkenmerken en het modelleren van innovatieprestaties.

Concepten en theorie

Innovatieprestatie (*innovation performance*) is één van de kernbegrippen die in hoofdstuk 2 worden gedefiniëerd. Innovatieprestatie is het vermogen van een organisatie om nieuwe kennis te creëren en op een economisch winstgevende manier toe te passen. Innovatieprestaties worden beïnvloed door zowel interne als externe factoren, die op meerdere ruimtelijke schalen werken. Technologieclusters zijn één van de belangrijkste ruimtelijke schalen waarop interacties tussen organisaties plaatsvinden (zoals tussen bedrijven en universiteiten). Op een hoger ruimtelijke schaalniveau beïnvloedt het nationale innovatiesysteem, dat regelgeving, financiering, nationale instellingen en beleid omvat, ook de innovatieprestaties. Echter, de toenemende globalisering heeft de invloed van nationale overheden sterk verminderd. Op mondiale schaal faciliteren interclusterkennisnetwerken leer-, samenwerkings- en andere kennisrelaties tussen clusters, hoewel deze relaties soms ongelijk zijn, wat kan leiden tot "omgekeerde" kennisstromen (*"reverse" knowledge flows*). Ook belangrijk is padafhankelijkheid: omdat kennis, ervaring, vaardigheden en relaties zich in de loop van de tijd opstapelen, kunnen reeds succesvolle technologieclusters goede innovatieprestaties vaak lange tijd voortzetten.

Er is aanzienlijke sectorale variatie in clusterkenmerken, ook in de sterkte en richting van het verband tussen clusterkenmerken en innovatieprestaties (positief of negatief). Deze verschillen zijn toe te schrijven aan de sectorale kennisbasis en ontwikkelingsfase: in sectoren met een technische- en ontwerpkennisbasis wordt ruimtelijke nabijheid belangrijk geacht omdat het de uitwisseling van stilzwijgende kennis (*tacit knowledge*) faciliteert. In sectoren met een wetenschappelijke kennisbasis lijkt kennisoverdracht over lange afstanden te worden vergemakkelijkt door het gebruik van meer gecodificeerde kennis. Sectoren in een opkomende fase hebben doorgaans een lagere padafhankelijkheid, schaarsere kennisnetwerken en een meer nieuwe clustervorming. Naarmate een sector en technologieclusters volwassener worden, nemen de agglomeratie en de omvang van kennisnetwerken toe. Ook nationaal beleid kan een rol spelen bij het ondersteunen van de creatie en groei van technologieclusters. Om een beter begrip te krijgen van de clusterkenmerken en innovatieprestaties van duurzaamheidstechnologieclusters, worden 12 hypotheses opgesteld, die in zes groepen kunnen worden verdeeld: (i) veranderingen in de wereldwijde ruimtelijke spreiding van technologieclusters (hypothese 1), (ii) sectorale verschillen (hypotheses 2 & 12), (iii) diverse aspecten van agglomeratie op cluster- en regionale schaal (hypotheses 3-5), (iv) nationaal innovatiesysteem (hypothese 6), (v) kennisstromen en kennisnetwerken (hypotheses 7-10) en (vi) padafhankelijkheid (hypotheses 11 en 12).

Data en methodologie

Een nieuw clusterinnovatieprestatiemodel, inclusief modelindicatoren en een nieuwe clusteridentificatiemethodologie, staan centraal in de hoofdstukken 3 en 4. Het clusterinnovatieprestatiemodel is een aanpassing van eerdere kennisproductiefuncties, waarin het verband tussen clusterkenmerken en innovatieprestaties wordt onderzocht. In dit onderzoek is de afhankelijke variabele een samengestelde indicator van octrooicitaten gedeeld door het aantal uitvinders. Citaten zijn een maatstaf voor de kwaliteit van octrooien (Hall, Jaffe, and Trajtenberg 2005) en de uitvinders zijn een maatstaf voor de aanwezige kennisbronnen. Deze aanpak modelleert met succes de clusterkenmerken die samenhangen met clusterinnovatieprestaties in diverse hightechsectoren, waaronder de duurzaamheidstechnologiesectoren. De onafhankelijke variabelen van het model beschrijven agglomeratie, het nationale innovatiesysteem, interclusterkennisnetwerken en padafhankelijkheid.

Technologieclusters worden geïdentificeerd met behulp van een nieuwe "warmtekaart"-methodologie die clusters identificeert op basis van octrooien. Deze aanpak geeft de werkelijke locatie van innovatieactiviteit weer en geeft een nauwkeuriger beeld van de ruimtelijke spreiding en clusterkenmerken dan het gebruik van bestuurlijke grenzen. De methodiek wijkt af van eerdere "organische" clusteronderzoeken (Catini et al. 2015; Alcácer and Zhao 2016; Bergquist, Fink, and Raffo 2017) op drie belangrijke punten: (i) er words één gegevensbron gebruikt, namelijk de octrooiverleningsdatabase van het United States Patent & Trademark Office, USPTO, om zo één standaard voor octrooibeoordeling te waarborgen (ii) een home bias correctie wordt toegepast om te compenseren voor verschillen in octrooi- en citatiefrequentie tussen de Verenigde Staten en andere landen en (iii) een Kernel Density Estimation-methode (Rosenblatt 1956; Parzen 1962) wordt gebruikt om een "warmtekaart" van ooctrooien te berekenen waaruit technologieclusters worden geïdentificeerd. Parameters zijn geoptimaliseerd om kleine clusters te detecteren en te voorkomen dat onrealistisch grote clusters worden gedetecteerd. De methodologie maakt het mogelijk om een unieke en nauwkeurige wereldwijde gegevensbank van technologieclusterstatistieken aan te leggen.

Resultaten: wereldwijde ruimtelijke verdelingspatronen

De sector gezondheidstechnologie wordt geanalyseerd in hoofdstuk 5 en bestaat uit twee technologische subsectoren: medische apparaten en medische levenswetenschappen. De sector duurzame energietechnologie wordt geanalyseerd in hoofdstuk 6 en bestaat uit zeven technologische subsectoren: biobrandstoffen, elektrische voertuigen, elektriciteitsopslag, brandstofcellen, waterstoftechnologie, zonne-energie en windturbines. De subsectoren behoren tot de meest innovatieve binnen hun respectievelijke sectoren en omvatten zowel subsectoren met een technische- en ontwerpkennisbasis (medische apparaten, elektrische voertuigen en windturbines) als een wetenschappelijke kennisbasis (medische levenswetenschappen, waterstoftechnologie, zonne-energie, enz.). Hoofdstukken 5 en 6 geven een beschrijvende analyse van de ruimtelijke spreiding, agglomeratie en kennisnetwerken van de sectoren, en een kwantitatieve analyse van het verband tussen innovatieprestaties en clusterkenmerken. Een vergelijkend perspectief tussen de sectoren wordt gepresenteerd in hoofdstuk 7, samen met een overzicht van mogelijke beleidstoepassingen.

De grootste technologieclusters (naar octrooiproductie) bevinden zich meestal in grote "wereld" steden zoals San Francisco, Tokio, New York en Los Angeles, hoewel het ruimtelijke patroon van duurzame energietechnologie anders is, aangezien ongeveer de helft van de 10 grootste clusters zijn te vinden in kleinere steden zoals Daejeon, Detroit, Nagoya en Stuttgart. In subsectoren zoals biobrandstoffen en windturbines zijn de grootste technologieclusters te vinden in kleine steden zoals Aarhus (Denemarken), Aurora (Colorado, Verenigde Staten) en Pamplona (Spanje). Dit bevestigt eerdere waarnemingen dat niche high-tech clusters zich kunnen ontwikkelen in relatief afgelegen locaties. Wereldwijd gezien is innovatie op het gebied van zorgtechnologie geconcentreerd in Noord-Amerika, terwijl duurzame energietechnologie geconcentreerd is in Azië (Japan, Zuid-Korea en Taiwan). Europa blijft achter, hoewel het in sommige deelsectoren, zoals windturbines, een leidende rol speelt.

De sector duurzame energietechnologie groeit snel, met 100 nieuwe clusters die tijdens de studieperiode zijn ontstaan. Nieuwe clusters onstaan in verschillende typen landen, zowel in innovatieleiders, zoals de Verenigde Staten, en in landen met een beperkter innovatievermogen, zoals Spanje en India. In absolute termen zijn de meeste clusters ontstaan in Noord-Amerika. Gedurende de onderzoeksperiode zijn de gemiddelde clustergrootte, het aandeel octrooien in clusters (*clustering rate*) en de intercluster kennisnetwerkdichtheid toegenomen in de duurzame energietechnologiesector. Daarentegen is het aantal gezondheidstechnologieclusters en hun agglomeratie- en kennisnetwerkkenmerken grotendeels onveranderd gebleven.

Onderzoek op het gebied van duurzame energietechnologie groeit in China, Denemarken, Frankrijk, Zuid-Korea, Taiwan en de Verenigde Staten, maar het neemt af (relatief gezien) in Canada, Duitsland, Japan en het Verenigd Koninkrijk. Onderzoek naar gezondheidstechnologie laat een ander patroon zien, met groei in China, Zuid-Korea en Taiwan, terwijl het aandeel van de Verenigde Staten en Japan stabiel is en het aandeel van Europese landen afneemt (relatief gezien). Dit suggereert dat er een "mondiale verschuiving" plaatsvindt van Europa naar Azië in de gezondheidstechnologiesector, terwijl de richting van mondiale verschuivingen complexer is voor duurzame energietechnologie.

Resultaten: Clusterinnovatieprestaties

De resultaten van het clusterinnovatieprestatiemodel geven nieuwe inzicht in de clusterkenmerken die samenhangen met innovatieprestaties, met name agglomeratie, het nationale innovatiesysteem, kennisnetwerken en padafhankelijkheid. Met betrekking tot agglomeratie bevestigen de resultaten een positief verband tussen schaalvoordelen (clustergrootte) en clusterabsorptievermogen (bedrijfsonderzoek). Agglomeratie-effecten verschillen echter wanneer een cluster relatief dicht bij andere grote clusters ligt ($<$ 200 km, aangrenzend effect, *adjacency*), een situatie die zich meestal voordoet als een cluster deel uitmaakt van een grotere agglomeratie. De duurzame energieclusters Utsunomiya, Mito en Chiba bevinden zich bijvoorbeeld allemaal binnen 200 km van Tokio en kunnen worden beschouwd als onderdeel van "Groot Tokio." Hoewel ruimtelijke nabijheid voordelen kan hebben, zoals toegang tot een diepere talentenpool en gespecialiseerde dienstverleners, lijkt de toegenomen concurrentie om talent en middelen deze voordelen te overtreffen op de schaal van grotere agglomeraties. Ook moet worden opgemerkt dat de negatieve associatie met het aangrenzend effect niet wordt gevonden in clusters van duurzame energietechnologie, vermoedelijk vanwege hun kleinere omvang en opkomende ontwikkelingsfase. De sector duurzame energietechnologie is ook uniek, omdat het nationale innovatiesysteem een statistisch significante invloed heeft op de innovatieprestaties van clusters in deze sector.

Toegang tot een groot aantal verschillende clusters (netwerkbereik) en uitgaande kennisstromen hangen positief samen met de clusterinnovatieprestaties in de gezondheidstechnologiesector. De uitstroom van kennis wordt gefaciliteerd door multinationale ondernemingen, en hun positieve relatie met innovatieprestaties ondersteunt de waarneming dat multinationale ondernemingen zich vaak vestigen in reeds succesvolle clusters (Awate, Larsen, and Mudambi 2015; Østergaard and Park 2015). De uitstroom van kennis is echter niet statistisch significant in de duurzame energietechnologiesector. Padafhankelijkheid heeft een positieve invloed op de prestaties van clusterinnovatie in alle sectoren, hoewel het verband zwakker is in de duurzame energiesector. De empirische resultaten laten duidelijke verschillen zien tussen de sector duurzame energietechnologie en gezondheidstechnologie.

Onderzoeksbijdragen

De onderzoeksbijdragen worden beschreven in hoofdstuk 8 en zijn van toepassing op vier hoofdgebieden: methodologie, nieuwe empirische resultaten, theorie en beleid. De methodologische bijdrage omvat de identificatie van technologieclusters uit octrooigegevens en de karakterisering van deze clusters met behulp van nieuwe indicatoren, waardoor een uitgebreid wereldwijd overzicht wordt verkregen van de technologieclusters en interclusterkennisnetwerken van een sector. Dergelijke informatie was voorheen moeilijk te verkrijgen en vormen daarom ook de belangrijkste empirische bijdrage van dit onderzoek. De theoretische bijdragen van het onderzoek is toegespitst op het aantonen van verschillen tussen gezondheidstechnologie en duurzame energietechnologie, verschillen die niet alleen aan hun ontwikkelingsfase kunnen worden toegeschreven. Hoewel de lagere padafhankelijkheid en het ontbreken van negatieve agglomeratie-effecten van de duurzame energietechnologiesector niet onverwacht zijn, heeft de sector ook een lagere invloed van bedrijfsonderzoek en wordt de sector sterker beïnvloed door nationale instellingen en beleid (nationaal innovatiesysteem). Dit verschil is waarschijnlijk te wijten aan de sociaal-technologische transitie die plaatsvindt in het energiesysteem, waarbij aanzienlijke invloed van maatschappelijke actoren plaatsvindt. Het ontbreken van deze invloeden in de gezondheidstechnologiesector suggereert dat de sociaal-technologische transities in de zorg sterk verschillen van die in de duurzame energie. De onderzoeksresultaten tonen ook dat relatief grote duurzaamheidstechnologieclusters in kleinere steden hoge innovatieprestaties mogelijk maken. Een dergelijke situatie lijkt profijt te hebben van lokale agglomeratie-economieën en voorkomt tegelijkertijd de schaalnadelen die optreden wanneer clusters zich in grote stedelijke agglomeraties bevinden. Dit resultaat zou ook van toepassing kunnen zijn op andere opkomende hoogtechnologische sectoren (Steen and Hansen 2018). Vanuit beleidsperspectief biedt de methodologie een nuttig instrument voor het monitoren van de opkomst en groei van technologieclusters, hun netwerken en belangrijke innovatieactoren, op wereldwijde schaal. Het onderzoek laat ook grote verschillen zien tussen sectoren, vooral op het gebied van duurzame energietechnologie. Beleid ter ondersteuning van de ontwikkeling van technologieclusters moet daarom worden aangepast aan de sector, inclusief de sociaal-technologische context.

Conclusie

Onderzoeksbeperkingen, reflecties en de conclusie worden aangereikt in hoofdstuk 9. De belangrijkste beperkingen zijn de selectie van de tijdsperiode en het modelontwerp dat, vanwege het gebruik van octrooigegevens, bepaalde theoretische concepten niet (goed) kan meten, maar die wèl verband houden met clusterinnovatieprestaties. Voorbeelden zijn ondernemerschap, sociaal kapitaal en beleidsprikkels. Deze beperkingen zouden in toekomstig onderzoek kunnen worden uitgediept door gedetailleerde clustercasestudy's uit te voeren. Ondanks deze beperkingen werpen de onderzoeksresultaten licht op het concept van clusterinnovatieprestaties, de aard van wereldwijde verschuivingen in innovatieactiviteit en verschillen in sociaal-technologische transities. In deze studie zijn innovatieprestaties geoperationaliseerd als een efficiëntie-indicator, maar slechts 30-60% van de clusterinnovatieprestaties kan door het model worden verklaard, en wordt voornamelijk verklaard door padafhankelijkheid. Mogelijke redenen hiervoor zijn dat de clusterinnovatieprestaties grotendeels afhankelijk zijn van de prestaties van specifieke technologische niches, en dat de groei van clusters vaak wordt gedreven door andere factoren, zoals de strategische commerciële en technologische beslissingen die buiten het model vallen. Wereldwijde verschuivingen in de ruimtelijke verdeling van clustervorming en -groei lijken nauw verband te houden met lokale factoren zoals de aanwezigheid van kennisinstellingen, investeringen en ondersteunend beleid. Hoewel landen als China, Zuid-Korea en Taiwan de ontwikkeling en groei van technologieclusters met succes hebben ondersteund, wordt vergelijkbaar beleid ook in andere delen van de wereld gevoerd, zij het op kleinere schaal en voor specifieke sectoren zoals duurzame energie.

Ook blijkt er een groot verschil te zijn tussen het soort sociaal-technologische transities die plaatsvinden in het energie- en zorgsysteem. In de energiesector vereist de invoering van nieuwe duurzame energietechnologieën fundamentele veranderingen in de bedrijfsmodellen van energieopwekking en -distributie. Maar in de gezondheidstechnologiesector lijken de bedrijfsmodellen grotendeels onveranderd. Deze verschillen blijken vooral uit het verband, of het gebrek daaraan, met bedrijfsonderzoek en het nationale innovatiesysteem, en zouden verder kunnen worden onderzocht door andere opkomende sectoren en tijdsperioden te bestuderen.

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