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## **High Technology Cluster Innovation Performance: A Global Perspective (1975-2019)**

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### **ABSTRACT**

This research explores the global development of four patent-rich high-technology sectors from 1975-2019 in terms of cluster formation trends, innovation performance, agglomeration and inter-cluster knowledge networks. The descriptive and explanatory analysis is framed within the context of sector- and cluster life cycle theories. The pharmaceuticals and semiconductor sectors are considered mature, while the information technology and solar photovoltaics sectors move from the initial exploration phase to growth, and then to a mature development phase during the study period. The empirical results show that agglomeration and knowledge network factors have a strong influence on cluster innovation performance right before, during and soon after the high-growth phase of the sectors. In the mature sectors, more recent periods show a positive influence of knowledge network factors and a negative influence of scale-bases agglomeration in the pharmaceuticals sector. The semiconductor sector shows a positive influence of network connectivity, which may partly explain the sector's high spatial concentration in clusters. These observations can be explained by long-term trends in these respective sectors.

Word count: 10,276

## 1. INTRODUCTION

The innovation performance of high technology clusters is of great importance for economic well-being, scientific progress, and increasingly, geo-strategic competition (such as between China and the United States) (Chen, Chen, and Dondeti 2020; Porter 2000). Innovation activity tends to be concentrated in a small number of globally dispersed locations. The growth (or decline) of a single cluster can therefore have far-reaching implications beyond its immediate location (Feldman and Kogler 2010; Malecki 2021), although knowledge about these implications remains scarce.

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 and Bessant 2014). Although there is a rich literature on high-technology clusters and the factors associated with high innovation performance, much of this knowledge comes from case studies, especially of highly successful clusters or groups of clusters (Saxenian 1996; Asheim and Coenen 2005; Hassink and Shin 2005; Esmaeilpoorarabi, Yigitcanlar, and Guaralda 2018). While these scientific contributions are very valuable, it is not clear if their conclusions can be generalized more widely across different high technology sectors, across different countries, or across different time-periods. Increasingly, the global importance of high technology clusters is being recognized, as cities, rather than the nation state, are seen as the spatial unit at which knowledge production and innovation take place (World Economic Forum 2018; Dutta et al. 2022). So far, systematic empirical studies that increase understanding of the variations in growth of high technology clusters, both in time and place, have been lacking.

Current theoretical work can be seen as contradictory. Taking agglomerations of people and firms as an example, on the one hand it can foster a larger local market, specialized suppliers, a deeper labor pool, mutual trust among actors and lower transaction costs (McCann 2013). On the other hand, agglomeration can also increase local competition for resources, raising prices of land and business accommodation, leading to diseconomies of scale (McCann 2013; Richardson 1995).

In other words, the factors that influence innovation performance vary. In the literature this variation in influence is typically explained by the knowledge base or development phase of a sector (Breschi 2000; Binz and Truffer 2017; Breschi and

Malerba 1997; Ter Wal and Boschma 2011). For example, agglomeration may be seen as more important in the early development phase of the sector, or in sectors that rely more on intangible knowledge (Ter Wal and Boschma 2011; Martin and Sunley 2011). As clusters mature, some researchers observe that the importance of agglomeration disappears (Ter Wal and Boschma 2011), while others, including many policy makers, do not view agglomeration advantages as a temporary phenomenon (Porter 2000; Martin and Sunley 2003). In order to shed light on all stages of the cluster lifecycle dimension, this paper considers the development of high-technology sectors over a period of more than four decades.

This research provides empirical insight into the global development of high technology clusters, their innovation performance, and the factors that are associated with it. The aim of the study is to understand "when" (in terms of sector or development phase) specific factors best explain cluster innovation performance. It also includes an analysis of the global shifts that occurred in the location of top clusters (Dicken 1998). The empirical analysis is based on 42 years of patent grant data from the United States Patent and Trademark Office (USPTO) from 1975 to 2021 and covers four global patent-rich high technology sectors with very different technological and socio-technological innovation profiles (Lim 2004; Geels et al. 2017). Semiconductors and pharmaceuticals are considered to be relatively mature throughout the study period. Information technology and solar photovoltaics are seen as emerging sectors which grow rapidly starting in the 1980s and 2000s, respectively.

The research addresses the following questions:

1. How does innovation performance change over time, including global shifts?
2. How do cluster agglomeration and knowledge network characteristics change over time?
3. How does the association between cluster innovation performance and agglomeration and knowledge networks change over time?

The paper begins with a literature review related to the drivers and changes in cluster innovation performance (section 2). This is followed by an outline of the methodology (section 3) and a presentation and analysis of the results (section 4).

The research findings are summarized in the concluding section, along with research limitation (section 5)

## **2. LITERATURE REVIEW**

In this review, perspectives and theories about the innovation performance of clusters and the related cluster and sector life-cycle models are addressed. The development of high technology research clusters and their innovation performance are influenced by a diverse range of factors, including agglomeration and knowledge networks. High technology clusters can be conceptualized as “locational subsystems” of global (sectoral) innovation systems (Binz and Truffer 2017). The development of clusters is therefore seen to be influenced by economic and technological changes that occur in the global sectoral innovation system (Breschi and Malerba 1997).

Within the context of a global sectoral innovation system, cluster innovation performance is also influenced by access to global knowledge networks (Bathelt, Malmberg, and Maskell 2004; Gertler and Wolfe 2006) and by internal cluster characteristics (agglomeration effects). Local agglomeration effects can include scale, but also the presence of specific actors such as universities (Etzkowitz 2012), trust, and social capital, and they can be both advantageous and disadvantageous to the cluster (Capello 2009; Nooteboom 2013; de Vaan, Frenken, and Boschma 2019). Especially in high-technology sectors, which tend to have a scientific knowledge base, the presence of university and government research institutes tends to be an important source of innovation through knowledge spillovers and by attracting talent (Asheim and Coenen 2005; Davids and Frenken 2018; Florida 1999).

Although local agglomeration and global knowledge networks are very different in their geographical reach, some of the advantages and disadvantages of agglomeration (“spatial proximity”) also appear to exist in the external knowledge networks of clusters, giving rise to the concept of “relational proximity”. Relational proximity is a kind of non-spatial agglomeration effect that describes how innovation actors are connected to partners outside the cluster in relationships that involve the transfer and co-creation of knowledge (Boschma 2005).

Within social network theory, having a privileged position within a network confers certain advantages, such as better access to knowledge being produced elsewhere

(Wasserman and Faust 1994). The centrality of a cluster within a knowledge network can be defined in different ways. It can be defined as the number of direct connections to other clusters (degree centrality, also referred to as *network density* in this study), or based on its *connectivity* to other highly connected nodes (eigenvector centrality), which takes into account the transitive influence that knowledge transfers are likely to have. Especially from the perspective of knowledge ownership (as secured through patents), having access to unique knowledge may be more advantageous. A strong *bridging* position (betweenness centrality) in a network with many structural holes (missing links between nodes) may place a cluster in a privileged position with regards to the flow of knowledge.

Complementing the systems and proximity perspectives, are evolutionary perspectives on cluster development, notably the related concepts of the sector and cluster life cycle (Boschma 2007; Martin and Sunley 2011). A simplified life cycle model is often presented in the literature, which identifies three or four phases. An initial development stage, during which experimentation occurs (“path formation”). A growth stage, during which knowledge is successfully exploited and expanded (“path creation”). A mature or decline phase, during which growth stagnates, which can lead to renewed experimentation and growth, or further decline and the eventual destruction of a cluster or sector (“path following”, “path lock-in” or “path breaking”) (Martin and Sunley 2011). A summary of how each phase influences the cluster and the sectoral innovation system is presented in table 1, below.

<b>Phase</b>	<b>Sectoral Innovation System</b>	<b>Cluster Dynamics</b>
Emergence (path formation)	New industry emerges, but still without agglomeration advantages or institutional support, creating a window of opportunity for new cluster creation (Boschma 2007). During this period, the innovation system is highly unstable, which is reflected in sectoral knowledge networks, clustering patterns and innovation performance (Ter Wal and Boschma 2011).	Exogenous shock or event (trigger) creates a cluster (Maggioni 2004). Examples include indigenous invention or combination of knowledge at a local university or research institute, industrial diversification, upgrading or transplantation from elsewhere (Martin and Simmie 2008). There is a high degree of uncertainty and experimentation. Clusters can

		also quickly disappear (Martin and Sunley 2011).
Growth (path creation)	Technology reaches sufficient maturity and a successful development path is found (Martin and Simmie 2008). The sectoral innovation system becomes more stable in terms of knowledge networks, and cluster agglomeration increases (Ter Wal and Boschma 2011).	Agglomeration advantages, such as a labor market specialization, supply of specialized intermediate goods, knowledge spillovers, etc. take hold, and drive the growth of the cluster (Maggioni 2004; McCann 2013).
Mature (path following or renewal)	Growth remains stable or slows down, and the importance of knowledge networks and cluster agglomeration decline as the technological path becomes stable, and firms compete by optimizing their existing knowledge (Ter Wal and Boschma 2011; Martin and Sunley 2011). The industry survives until it is replaced by an alternative technology (Geels 2005).	Cluster achieves positive path lock-in, whereby skills, experience and institutional advantages accumulate, creating a sustainable competitive advantage. Or, rising competition from other clusters (or industries), leads to the cluster's eventual decline and destruction (Martin and Simmie 2008; Maggioni 2004), unless the cluster is able to find a pathway for renewal (Menzel and Fornahl 2010)

**Table 1:** Summary of theoretical perspectives on sector and cluster life cycle.

Based on the theoretical understandings summarized in table 1, certain expectations can be formulated about how sectors develop over time in terms of their spatial distribution and knowledge networks, and whether these factors influence<sup>1</sup> cluster innovation performance. These expectations are summarized in table 2.

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<sup>1</sup> “Influence” implies causality. While there is evidence suggesting that factors such as agglomeration and knowledge networks have a causal influence on innovation performance, we recognize the possibility of reverse-causality or mutual-causality, as has been noted in the R&D-patenting relationship (Baraldi, Cantabene, and Perani 2014).

The expectations encompass three development phases (path formation, creation and following/renewal) and can be divided into two types: expectations regarding the *spatial distribution and knowledge network structure* of high technology clusters and expectations about the *influence of agglomeration and knowledge network factors* on the innovation performance of clusters. The spatial distribution and knowledge network structure are formulated in terms of the number of clusters, clustering rate (share of innovation activities that takes place in clusters), and the density of knowledge networks. The influence of agglomeration and knowledge networks is expected to be similar: both weak during the path formation phase, strong during path creation, and weakening once more during the path following or renewal phase.

<b>Phase</b>	<b>Spatial distribution and knowledge network structure</b>	<b>Influence of agglomeration and knowledge network factors</b>
Emergence (path formation)	Number of clusters: <i>few</i> Clustering rate: <i>low</i> University and government patent share: <i>high</i> Knowledge networks: <i>sparse</i>	<i>Weak</i> (no influence)
Growth (path creation)	Number of clusters: <i>increasing</i> Clustering rate: <i>high</i> University and government patent share: <i>decreasing</i> Knowledge networks: <i>densifying</i>	<i>High</i>
Mature (path following or renewal)	Number of clusters: <i>stable</i> Clustering rate: <i>stable or decreasing</i> University and government patent share: <i>low</i> Knowledge networks: <i>stable</i>	<i>Low</i>

**Table 2:** Simplified model of sector and cluster development (expected trends).

### 3. DATA, INDICATORS AND RESEARCH MODEL

This section provides an overview of the patenting data, patent location (geocoding), time aspects, technical corrections, cluster identification process and the calculation of innovation indicators. The empirical part of this research is based on publicly available patent grant and patent citations data from the USPTO for the years 1976-2021.<sup>2</sup> Patent data for specific sectors is selected based on Cooperative Patent Classification (CPC) codes based on the classifications by the World Intellectual Property Organization (WIPO) (Schmoch 2008), or the CPC codes for climate change mitigation technologies (Palumbo 2013; Leydesdorff et al. 2015). Four research intensive sectors are chosen which produce a large number of patents. Information technology and solar photovoltaics are considered to be growth sectors, whereas semiconductors and pharmaceuticals are more mature during the study period. An overview of the sectors and the number of patent grants is shown in table 3.

Sector	CPC codes	Patent grants (1975-2019)
Information technology	G06; G11C; G10L	170,321
Semiconductors	H01L; B81	481,751
Pharmaceuticals	A61K; A61P	309,354
Photovoltaics	Y02E 10/5	33,539

**Table 3:** Overview of four sectors.

To identify the location of inventors and patent assignees (patent owners) their address data is used (usually city, state and country). Although the patent database provides coordinates for addresses, these appear to have limited accuracy, especially outside of the United States. Therefore the open source Pelias Geocoder<sup>3</sup> is used to geocode addresses from all countries and territories and all U.S. states with an area of *more than* 20,000 km<sup>2</sup>. Countries, territories and states which are smaller than 20,000 km<sup>2</sup> are directly assigned standard coordinates. This approach saves processing time and avoids geocoding errors related to place names.

<sup>2</sup> Downloaded from the USPTO's PatentsView website (<https://patentsview.org/download/data-download-tables>). Data released on 7 March 2022. Data accessed on 29 September 2022.

<sup>3</sup> See the official project website at <https://pelias.io>. Accessed 24 October 2022.



Examples of directly-geocoded places are: Fiji, Jamaica, New Caledonia, Qatar and Singapore, as well as the states of Massachusetts and Hawaii.

The dataset is divided into 41 periods of five years, from 1975–2019 based on the patent application date. As patents take some time from application to grant, 2019 is the latest application year for which relatively complete patent grant data is available. All data is processed using R (R Core Team 2022) using a 5-year moving average period for each year.

When using a national patent database such as the USPTO, the home bias effect must always be considered (Bacchiocchi and Montobbio 2010). To gauge the degree of over-representation of patents with American inventors in the USPTO patent grant database, it is useful to compare patenting by Japanese and American inventors at both the European Patent Office (EPO) and the USPTO. Japan provides a useful comparison because it is regarded as the country with the greatest technological similarity to the United States (Toivanen and Suominen 2015; Mancusi 2008). According to the OECD Patents Statistics database<sup>4</sup>, between 1977–2017, Japanese inventors received 1,268,723 USPTO grants and 362,702 EPO grants (a ratio of 3.50:1), whereas American inventors received 3,370,025 USPTO grants and 482,323 EPO grants (a ratio of 7:1). This suggests that relative to Japanese patents, US patents are overrepresented in the USPTO database by a ratio of 2:1. Although this ratio fluctuates between 1977–2017, the annual median value is 1.94, which appears robust. Therefore, for each US location, the number of patents is divided by 2 to ensure a globally representative weighting. Other indicators are *not* adjusted, but in the model estimations a US dummy variable is included to adjust for the home bias effect.

Clusters are identified using the DBSCAN algorithm (Schubert et al. 2017) as implemented in the *dbscan* library of R (Hahsler, Piekenbrock, and Doran 2019). DBSCAN has been used by other researchers to identify clusters from patent data (Bergquist, Fink, and Raffo 2017; Dutta et al. 2022). Clusters are identified using a search radius of 0.2 degrees (approximately 22 km) with a minimum cluster size of 0.5% of the total patents in each period.<sup>5</sup> These values give realistic results across

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<sup>4</sup> See the OECD Statistics website at <https://stats.oecd.org>. Accessed 12 November 2022.

<sup>5</sup> The Global Innovation Index (Dutta et al. 2022) also uses DBSCAN, with a search radius of 15 km and minimum cluster size of 4,500 (0.1% of 4.5 million documents used). From this more than 230 clusters are identified, which is possible because of the larger dataset.

all sectors in terms of the number of clusters identified and their minimum size. Clusters must have a minimum of 10 inventors to be included in the analysis. Cluster indicators, as shown in table 4, are calculated from the patent data belonging to each cluster. Network indicators are calculated using the *igraph* library of R (Csardi and Nepusz 2006).

<b>Indicator</b>	<b>Unit</b>	<b>Measurement definition</b>
Innovation Performance (IVP)	Citations per inventor	<i>Dependent variable.</i> $IVP = CIT/INV$ , where CIT is the number of citations received by cluster patents (inventor weighted) and INV is defined below (Stek 2018; 2022).
Inventors (INV)	Inventor number	INV is the number of unique inventor names with addresses inside the cluster.
University and government research (UGR)	%	Share of patents in the cluster with at least one assignee identified as a university <sup>6</sup> or government institution (Stek 2018; 2022).
Co-inventor network density (CND)	Links per inventor	Co-invention network simple degree centrality. Network is derived from patents with inventors in two or more clusters.
Co-inventor network connectivity (CNC)	Weighted links	Co-invention network eigenvector centrality. Network is derived from patents with inventors in two or more clusters.
Inventor-assignee network bridging (IAB)	Weighted links	Inventor-assignee network betweenness centrality. Directed network is derived from patents with inventors in one cluster and assignees in one or more other clusters.

**Table 4:** Cluster indicators.

Overall, the indicators are both descriptive cluster characteristics, whose changes can be observed over time, and explanatory variables in the estimation of a simple cluster innovation performance model. The model consists of the abovementioned dependent variable (IVP), five independent variables and two dummy variables. A

<sup>6</sup> Government ownership of patents is indicated in the USPTO database. To identify universities a list of words (or word-parts) is used, see appendix A.

dummy for US clusters ( $D_{US}$ ) is included to account for the home bias effect (Bacchiocchi and Montobbio 2010) and a sector dummy ( $D_{SEC}$ ) is included to account for sectoral differences in citation and inventor patterns. The error term in the models is marked by  $\varepsilon$ .

$$IVP = D_{SEC}(\alpha + \beta_1 INV + \beta_2 UGR + \beta_3 CND + \beta_4 CNE + \beta_5 ANB + \beta_6 D_{US}) + \varepsilon$$

The model is evaluated for five different periods (the identification of these periods is discussed in section 4) using ordinary least squares (OLS) estimation. The models do not have any multicollinearity issues ( $VIF < 2.5$ ), model residuals appear to be normally distributed (Shapiro Wilk  $p < 0.01$ ) and there is no indication of heteroscedasticity (Breusch Pagan  $p < 0.01$ ). The model estimations have good predictive power, adjusted  $R^2$  varies from 0.671 to 0.865. The complete model estimation results, together with basic model diagnostics, are shown in table 5, and are discussed in section 5.

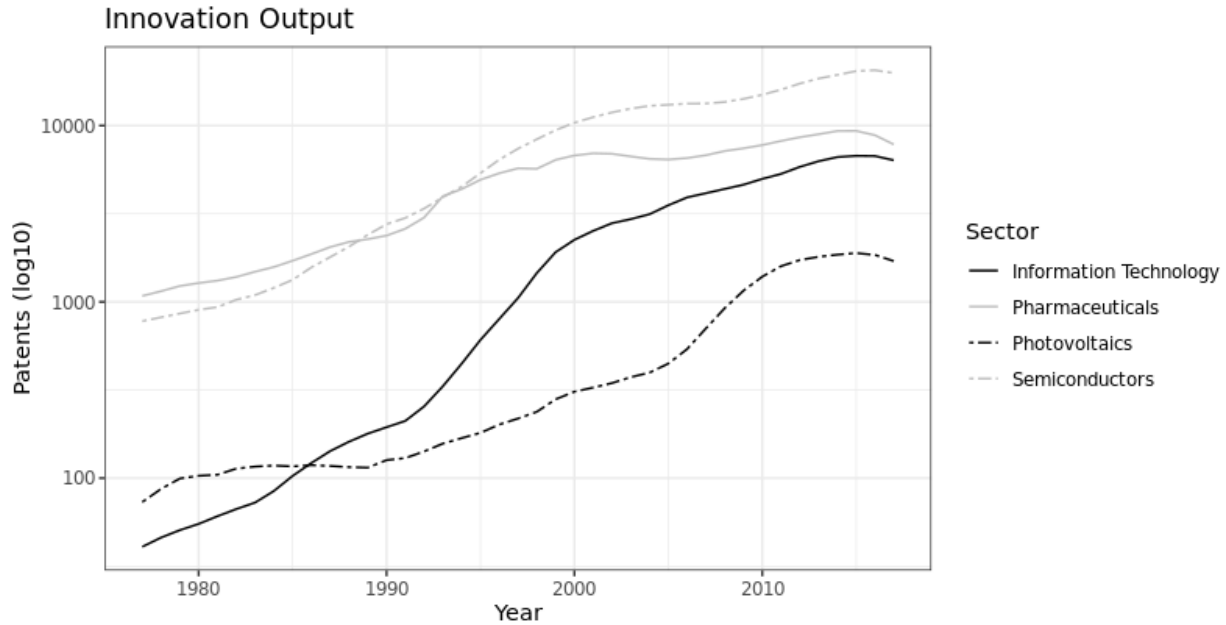
#### **4. RESULTS AND ANALYSIS**

The results and analysis are presented in three parts. First, the changing spatial distribution of innovation output and performance are explored (section 4.1). This is followed by an analysis of shifts in university-government research and knowledge network structure (section 4.2). Finally, the model estimation results are presented, showing changes in the influence of different factors over time (section 4.3).

##### *4.1 Spatial Distribution of Innovation Output and Performance*

Innovation output, as measured by the number of patent grants, shows clear differences in the growth trajectories of the four sectors (figure 1). The pharmaceuticals and semiconductor sectors appear as mature sectors throughout the study period, showing sustained growth. However, the growth rate appears to slow after 2000. The other two sectors, information technology and photovoltaics, appear to be emerging from 1977-1990 (period I), producing less than 300 patent grants per year. From 1991-1998 (period II) the information technology sector experienced accelerated growth, while patent output for the photovoltaics sector lagged. From 1999-2004 (period III) growth in the information technology sector decelerated, however from 2005-2012 (period IV) the photovoltaics sector experienced accelerating growth, which decelerated from 2013-2017 (period V). Thus, the information technology sector appears to experience an exploration

phase (1977-1990; period I), a growth phase (1991-1998; period II) and a mature phase (1999-2017; periods III-V). Similarly, the photovoltaics sector appears to experience an exploration phase (1977-2004; periods I-III), a growth phase (2005-2012; period IV) and a mature phase (2013-2017; period IV). A summary of these periods and the growth phases of information technology and photovoltaics is provided in table 5, and are also used for the model estimations (table 7).



**Figure 1:** Innovation output (patent grants, five-year moving average).

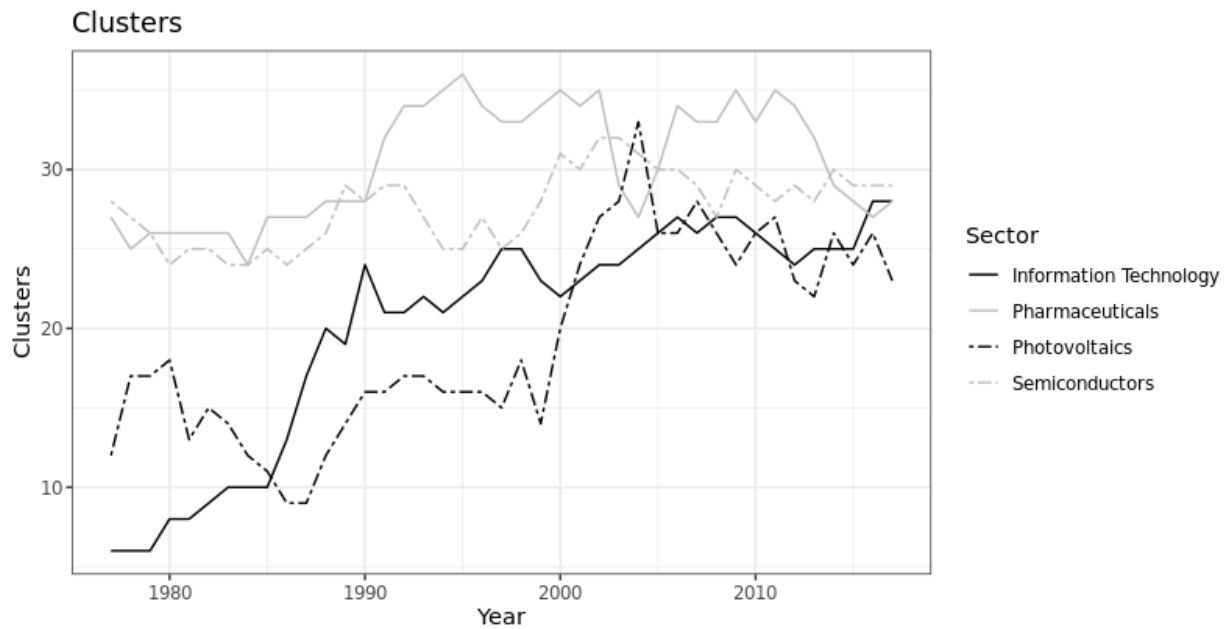
<b>Sector</b>	<b>Period I</b> (1977-1990, 14 years)	<b>Period II</b> (1991-1998, 8 years)	<b>Period III</b> (1999-2004, 6 years)	<b>Period IV</b> (2005-2012, 8 years)	<b>Period V</b> (2013-2017, 5 years)
Information Technology	<i>Emergence phase</i>	<i>Growth phase</i>	<i>Mature phase</i>		
Photo-voltaics	<i>Emergence phase</i>			<i>Growth phase</i>	<i>Mature phase</i>

**Table 5:** Periods reflecting the respective growth phases of the information technology and photovoltaics sectors.

Coinciding with the growth of patent output is an increasing number of clusters for the information technology and photovoltaics sectors (figure 2). The number of clusters appears to increase as a prelude to the high growth phase of the sectors

observed in 1991-1998 (period II; information technology) and 2005-2012 (period IV; photovoltaics). For photovoltaics, the number of clusters varies considerably, reaching as high as 17 and as low as 9 before the growth phase starting in 2005.

The total number of clusters detected for all sectors at the end of the study period is relatively similar, and falls within the 20-30 range. Although the number of clusters detected is influenced by the use of the DBSCAN algorithm and the cut-off of 10 inventors per cluster and 0.5% of global patent output, the spatial distribution of the four sectors seems to evolve towards an equilibrium of  $25 \pm 5$  globally significant clusters in each sector. Such an outcome could be due to clusters reaching certain limits in terms of the benefits of spatial and relational proximity. The growth of individual clusters could be limited by diseconomies of scale. Smaller clusters may lack the scale needed to maintain a strong position within global knowledge networks.



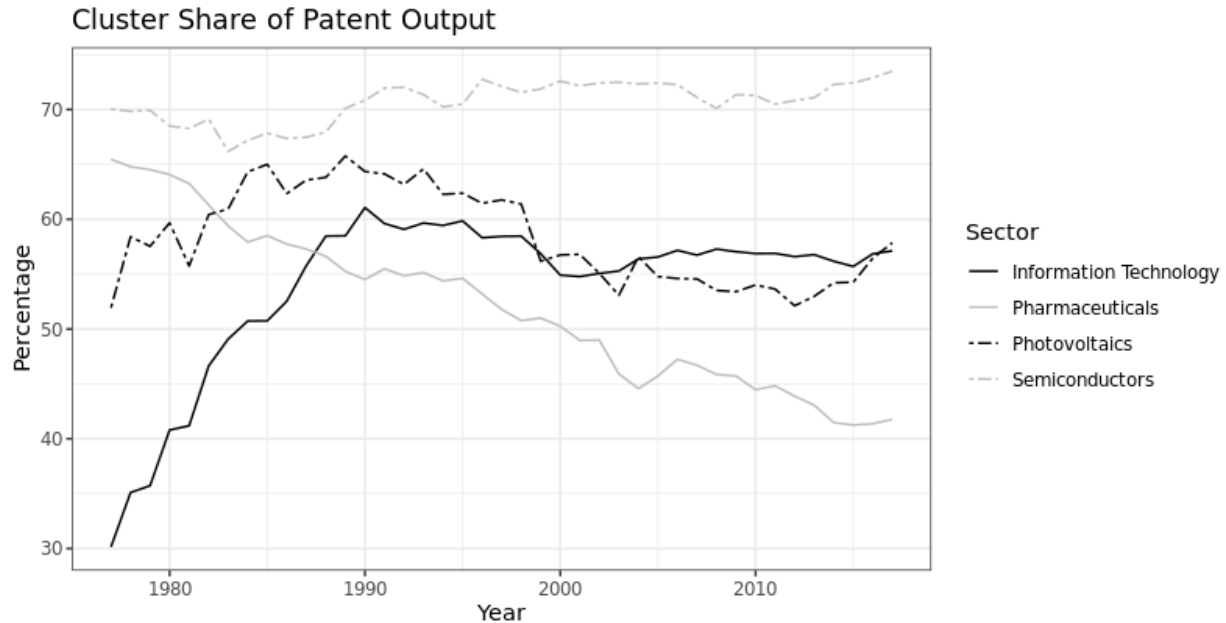
**Figure 2:** Number of clusters (calculated over moving five-year periods).

The four sectors show notable differences in terms of the cluster share of patent output (figure 3). For semiconductors this share remains consistent and high at approximately 70%, while for photovoltaics it varies across a broader range, between 52-66%. Yet information technology shows a clear path of increased concentration until the start of its high-growth period around 1991; the number of clusters appears to be closely correlated to the cluster share. For pharmaceuticals

the trajectory differs again: the number of patents produced from clusters sees a sustained decline from 65% in the late 1970s to 41% in the mid 2010s.

In some cases, the clustering rates observed seem to be related to the number of clusters, and thus the development phase of the sector. This seems to be the case for information technology and semiconductors, and follows the expectations outlined in table 2. The sustained decline in the clustering rate of pharmaceuticals could be partly driven by diseconomies of scale (Ter Wal and Boschma 2011), but also by the highly codified nature of the pharmaceuticals knowledge base which facilitates knowledge transfers over long distances (C. Park 2022; Gertler and Wolfe 2006). A further possible reason for the declining clustering rate is the increasing participation of university and government research institutions in pharmaceutical research (see figure 6). These institutions may be located outside of major clusters, and their research is commercialized in other locations (Buenstorf and Schacht 2013).

The clustering rate observed for solar photovoltaics is more difficult to comment on, except that it does not follow the observations for the other growth sector, information technology. The sector shares some of its technological base with semiconductors, and as shown in figure 6, also has a higher involvement from university and government research as compared to information technology and semiconductors.



**Figure 3:** Share of patent output in clusters (clustering rate, calculated over moving five-year periods).

Global shifts in innovation performance can be observed based on the location of each sector’s 10 largest clusters (table 6). All sectors appear to show an increase in top-10 clusters located in Asia (outside Japan) and a decline in top-10 clusters from Europe and Japan, and to a lesser extent, the United States. The United States is especially interesting, because it sees both declining clusters (such as Ploughkeepsie in semiconductors, a town located north of New York City) and rising clusters (such as Boston in pharmaceuticals). Seoul, Korea is illustrative of the rise of Asian clusters. During period I (1977-1990) it is not among the top-10 clusters in a single sector. By period V (2013-2017) it is among the top-10 clusters in all four sectors included in this research. Paris, France is illustrative of the decline of European clusters. During period I (1977-1990) it was among the top-10 clusters in all sectors. By period III (1999-2004) and later periods, Paris was only a top-10 cluster in one sector, pharmaceuticals. In fact, Paris, Frankfurt, Munich and London all held high positions in one or two sectors during period I, and have disappeared from the top-ten clusters in the most recent period.

Aside from Seoul, Hsinchu, Taiwan and Tel Aviv, Israel also gained ground in more than one sector even though they do not appear in the top-10 during period I (1977-1990). During the most recent period (V, 2013-2017), a number of new clusters

from emerging economies entered the top 10, including Bangalore, India (information technology) and Beijing, China (semiconductors and photovoltaics).

Although there are changes in the rank of clusters between periods, the top-10 generally sees a change of 2 or 3 clusters from period to period. The exception is the photovoltaics sector, which sees around 4 clusters change during each period, suggesting a much more dynamic spatial distribution. This observation aligns with the expectations for an emerging sector (see also table 2).

A number of cluster shifts can be linked to the performance of key corporations. In information technology, the rise of Seattle, United States is closely connected to the growth of Microsoft and later, Amazon. In semiconductors, the decline of Poughkeepsie, United States is connected to IBM shifting activities elsewhere whereas the rise of Hsinchu, Taiwan (TSMC, United Microelectronics, Realtek, etc.), Dallas, United States (Texas Instruments) and Gyeonggi, Korea (Samsung, Hynix) are likely connected to the success of anchor firms in these clusters, which also support a large local supplier ecosystem.

When comparing the cluster rankings for the most recent period (V, 2013-2017) to the Global Innovation Index clusters (Dutta et al. 2022), the results are similar in the sense that the top-10 clusters are mainly found in Japan, Korea, China and the United States. Some cities, such as Bangalore, Basel and Tel Aviv, do not appear in the top-20 of the Global Innovation Index cluster list, which is likely due to the high degree of specialization of those clusters in specific sectors such as information technology or pharmaceuticals. On the other hand, Chinese clusters such as Shenzhen and Shanghai are among the top-10 clusters in the Global Innovation Index, but they do not feature among the top-10 in this study. A likely reason for this is that Dutta et al. (2022) combine Shenzhen with Guangzhou and Shanghai with Suzhou (cities which are 80-100 km apart, approximately 20-30 minutes travel time by high speed train). Furthermore, the Global Innovation Index uses patent *and* scientific publication data, whereas the present study uses only patent data.

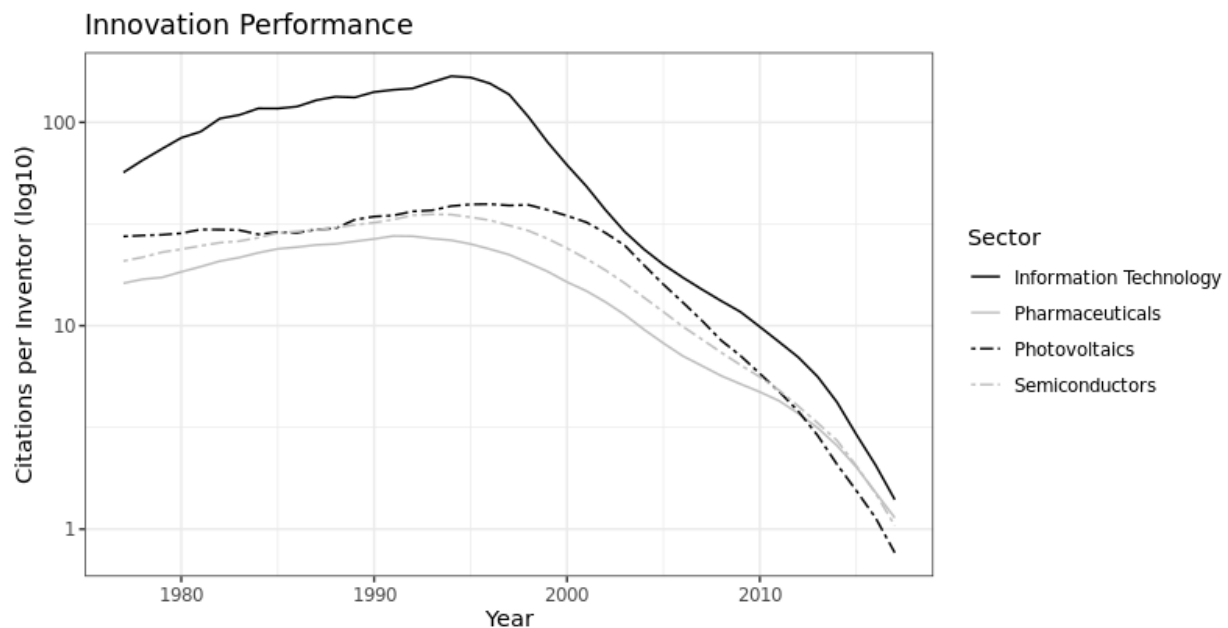


<b>Period</b>	<b>Rank</b>	<b>Information Technology</b>	<b>Semiconductors</b>	<b>Pharmaceuticals</b>	<b>Photovoltaics</b>
I (1977-1990)	1	Tokyo JPN (17)	Tokyo JPN (26)	New York USA (9.0)	Tokyo JPN (20)
	2	Nara JPN (10)	Osaka JPN (6.4)	Tokyo JPN (7.0)	Osaka JPN (9.7)
	3	New York USA (6.1)	San Jose USA (4.3)	Osaka JPN (5.2)	Los Angeles USA (6.5)
	4	Paris FRA (4.3)	Princeton USA (3.2)	Paris FRA (5.1)	Princeton USA (5.6)
	5	Nagoya JPN (2.3)	Munich DEU (2.8)	Frankfurt DEU (4.2)	Boston USA (3.7)
	6	Boston USA (2.2)	Poughkeepsie USA (2.4)	London GBR (4.1)	Munich DEU (3.0)
	7	San Jose USA (2.0)	Dallas USA (2.3)	Cologne DEU (2.8)	Washington USA (2.6)
	8	Chicago USA (2.0)	Paris FRA (2.1)	Milan ITA (2.8)	Detroit USA (2.6)
	9	Dallas USA (1.9)	Kobe JPN (1.9)	Basel CHE (2.5)	Paris FRA (1.9)
	10	Los Angeles USA (1.6)	Los Angeles USA (1.8)	San Francisco USA (2.2)	San Jose USA (1.8)
II (1991-1998)	1	Tokyo JPN (15.3)	Tokyo JPN (26)	New York USA (5.0)	Tokyo JPN (21)
	2	New York USA (9.7)	Osaka JPN (7.2)	San Francisco USA (4.6)	Osaka JPN (16)
	3	San Jose USA (7.3)	San Jose USA (6.4)	Tokyo JPN (3.9)	Nagahama JPN (4.1)
	4	Dallas USA (3.1)	Hsinchu TWN (5.3)	Boston USA (3.8)	Kyoto JPN (3.1)
	5	Boston USA (2.8)	Seoul KOR (2.7)	Paris FRA (3.7)	Boston USA (2.4)
	6	Chicago USA (2.2)	Kobe JPN (2.4)	Philadelphia USA (3.1)	Munich DEU (2.4)
	7	Washington USA (2.1)	Dallas USA (2.4)	Osaka JPN (2.6)	Nara JPN (1.7)
	8	Paris FRA (2.0)	Boise USA (2.3)	London GBR (2.3)	Denver USA (1.6)
	9	Seattle USA (1.8)	Taipei TWN (1.7)	Washington USA (2.0)	Los Angeles USA (1.4)
	10	Osaka JPN (1.7)	Poughkeepsie USA (1.7)	Frankfurt DEU (1.5)	Detroit USA (1.2)

III (1999-2004)	1	Tokyo JPN (11)	Tokyo JPN (21)	San Francisco USA (4.5)	Tokyo JPN (16)
	2	San Francisco USA (9.1)	Hsinchu TWN (8.4)	New York USA (4.3)	Osaka JPN (12)
	3	New York USA (6.8)	San Jose USA (7.0)	Tokyo JPN (3.6)	Kyoto JPN (4.2)
	4	Seattle USA (3.3)	Kyoto JPN (4.9)	Boston USA (3.6)	San Jose USA (3.2)
	5	Los Angeles USA (2.7)	Seoul KOR (4.2)	Paris FRA (2.9)	Los Angeles USA (2.3)
	6	Washington USA (2.5)	Boise USA (2.9)	Osaka JPN (2.6)	Boston USA (1.7)
	7	Boston USA (2.3)	Nagano JPN (2.1)	Philadelphia USA (2.5)	Kobe JPN (1.3)
	8	Atlanta USA (2.0)	New York USA (1.6)	London GBR (2.2)	Frankfurt DEU (1.1)
	9	Dallas USA (1.9)	Singapore SGP (1.5)	Washington USA (1.6)	Princeton USA (1.1)
	10	Austin USA (1.6)	Chiba JPN (1.4)	Tel Aviv ISR (1.4)	Tsukuba JPN (1.1)
IV (2005-2012)	1	San Francisco USA (12.8)	Tokyo JPN (20)	San Francisco USA (4.4)	Tokyo JPN (11.3)
	2	New York USA (5.7)	Seoul KOR (10)	New York USA (4.0)	Seoul KOR (8.9)
	3	Tokyo JPN (5.6)	Hsinchu TWN (7.8)	Boston USA (3.9)	San Jose USA (7.8)
	4	Seattle USA (5.1)	San Jose USA (4.8)	Tokyo JPN (3.7)	Osaka JPN (5.9)
	5	Los Angeles USA (3.2)	Osaka JPN (3.9)	Paris FRA (2.2)	Hsinchu TWN (4.1)
	6	Chicago USA (2.5)	Nagano JPN (2.6)	Basel CHE (1.9)	Frankfurt DEU (2.0)
	7	Boston USA (2.4)	Gyeonggi KOR (2.5)	Tel Aviv ISR (1.9)	Daejeon KOR (1.4)
	8	Washington USA (1.8)	New York USA (1.9)	Philadelphia USA (1.7)	Boston USA (1.4)
	9	Atlanta USA (1.7)	Singapore SGP (1.6)	Osaka JPN (1.6)	Los Angeles USA (1.1)
	10	Heidelberg DEU (1.6)	Nagoya JPN (1.3)	Seoul KOR (1.5)	Tsukuba JPN (1.1)
V (2013-2017)	1	San Francisco USA (16)	Tokyo JPN (15)	Boston USA (5.2)	Seoul KOR (13.2)
	2	Tokyo JPN (5.1)	Seoul KOR (12)	San Francisco USA (4.4)	Tokyo JPN (11.1)
	3	Seattle USA (4.5)	Hsinchu TWN (10.6)	New York USA (3.7)	San Jose USA (5.5)
	4	New York USA (3.4)	San Jose USA (4.2)	Tokyo JPN (3.0)	Osaka JPN (4.4)
	5	Los Angeles USA (2.9)	Osaka JPN (3.9)	Seoul KOR (2.3)	Daejeon KOR (2.6)
	6	Seoul KOR (2.3)	Beijing CHN (3.0)	Philadelphia USA (1.7)	Beijing CHN (2.5)
	7	Boston USA (2.1)	Nagoya JPN (2.1)	Tel Aviv ISR (1.6)	Hsinchu TWN (2.2)
	8	Bangalore IND (2.0)	Albany USA (1.9)	San Diego USA (1.6)	Frankfurt DEU (1.3)
	9	Tel Aviv ISR (1.9)	New York USA (1.6)	Paris FRA (1.5)	New York USA (1.2)
	10	Chicago USA (1.8)	Gyeonggi KOR (1.5)	Basel CHE (1.4)	Tel Aviv ISR (1.0)

**Table 6:** 10 largest clusters by sector and period (patent share).

In addition to the spatial distribution of innovation output, the overall decline in innovation performance, as measured by the number of citations per inventor (figure 4), should also be noted. Although inter-temporal changes in citation behavior is an area of scientific debate, and citations take time to accumulate (Sampat, Mowery, and Ziedonis 2003), the decline in observed citation rates appears to be more structural. All sectors see relatively stable innovation performance until approximately 1995-2000, when a rapid decline begins. This observation may be due to an overall decline in disruptive research findings in recent decades, a phenomenon that is observed across different fields of science, both in patents and scientific papers (M. Park, Leahey, and Funk 2023).



**Figure 4:** Innovation performance (five-year moving average).

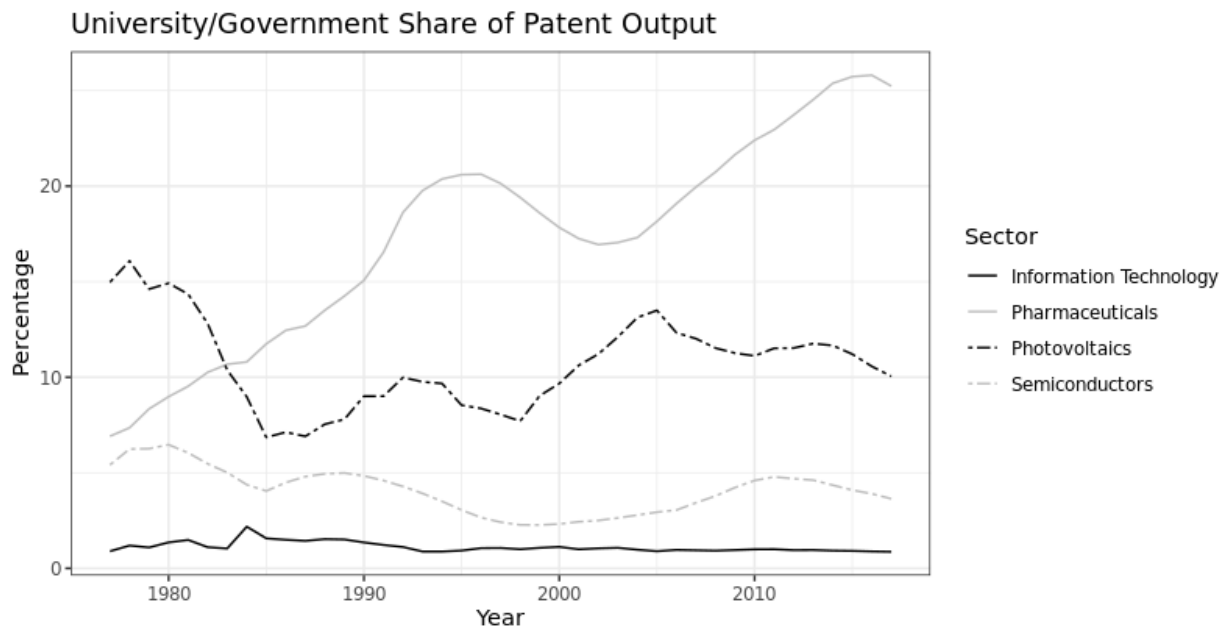
#### 4.2 University-Government Research and Knowledge Network Structure

Moving from the spatial analysis of clusters and cluster innovation performance, now some of the factors influencing cluster creation and cluster innovation performance are addressed, namely university-government research and the structure of knowledge networks.

As noted in the previous section, university-government research may partially influence the spatial distribution of innovation in the pharmaceuticals sector. Pharmaceuticals has the largest share of university-government research, rising to

around 25% in 2015 (figure 6). Interestingly, the share of university-government patenting in pharmaceuticals was below 10% in the late 1970s, but shows a growing interest in research commercialization by universities over time. This change is likely driven in part by regulatory changes, including the 1980 Bayh-Dole Act in the United States (Sampat, Mowery, and Ziedonis 2003) and the fact that the knowledge base of pharmaceuticals is heavily science-based (Tidd and Bessant 2014; Asheim and Coenen 2005).

The solar photovoltaic sector shows a different path, with relatively high initial participation by government and universities (more than 15% in the late 1970s) which then falls back until 1997, when the Kyoto Protocol is signed and public interest and investment again increase (Popp, Hascic, and Medhi 2011). This increase lasts until around 2005, when the sector begins its high-growth stage and government and university research continues to grow in absolute terms, but falls in relative terms due to increased private sector participation. In this way the photovoltaics sector behaves as assumed in table 2.



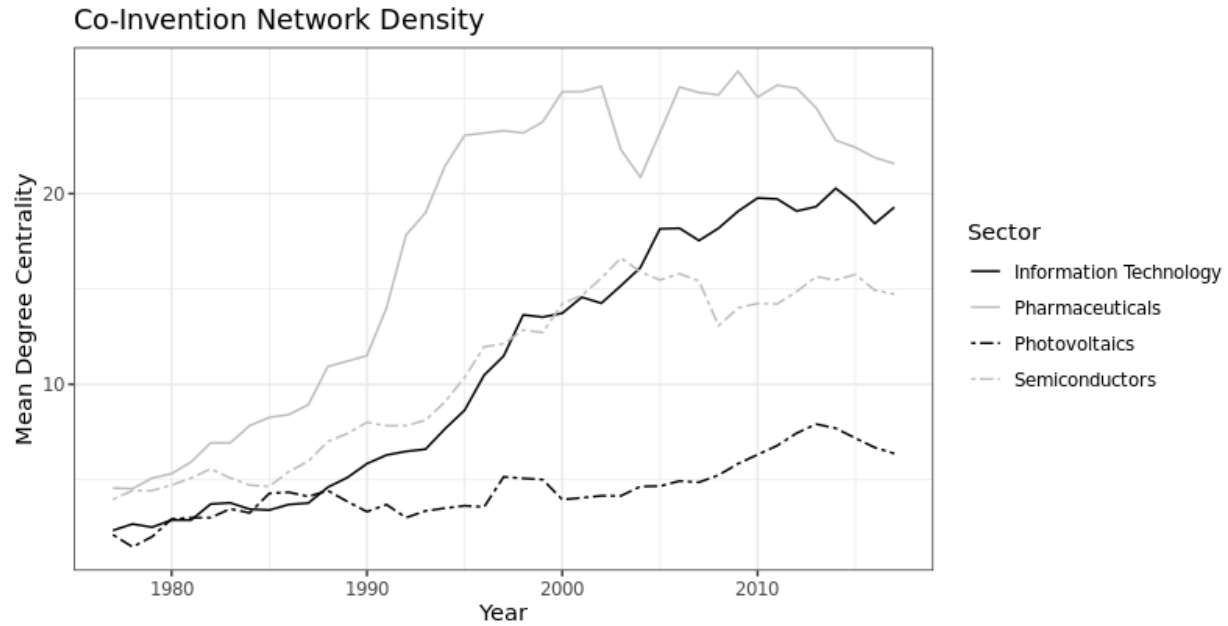
**Figure 6:** Changes in university-government patenting rate as a percentage of total patenting (calculated over moving five-year periods).

The development of knowledge network structure also follows a notable path, with the density of networks increasing over time (figure 7). Especially after 1990,

following the widespread adoption of the internet, there appears to be an acceleration in the density of inter-cluster networks. For example, the average number of unique connections of pharmaceutical clusters rose from 12 in 1990, to 23 in 1995.

The networks of the other sectors appear to grow at a slower rate. For the information technology sector this can be explained by its low number of clusters before 1990, and the lag that is often observed between cluster formation and the creation of network linkages (see also table 1 and 2) (He and Fallah 2009; Ter Wal and Boschma 2011). In the semiconductor sector, the slower network growth and a less dense network overall, are likely related to specific sectoral characteristics, including the higher clustering rate (see figure 3). In general, the growth of cluster networks since 1990 is attributed to a both technological developments and a shift towards greater technological specialization (Turkina, Van Assche, and Kali 2016)

The delayed growth of the photovoltaics network could be due to the relative newness of the sector and its smaller size, as a certain number of inventors and absorptive capacity is needed to sustain and benefit from network linkages (see also table 3) (Abreu 2011; Belso-Martínez, Expósito-Langa, and Tomás-Miquel 2016). The slow growth of inter-cluster linkages in renewable energy has also been noted in earlier research, and is partly attributed to a lack of suitable institutional support (Negro, Alkemade, and Hekkert 2012).



**Figure 7:** Changes in average network density (links per cluster, calculated over moving five-year periods).

The increase in knowledge network density (CND) mirrors the expansion in average network connectivity (CNC). However, the inventor–assignee network bridging (IAB) indicator does not show a clear trend for any of the sectors. This suggests that certain clusters retain a relatively strong position as research investors in other clusters, for example in the case of multinational corporations maintaining remote labs (Montobbio and Sterzi 2013).

#### 4.3 Cluster Innovation Performance Model

After the descriptive analysis of the previous two subsections, the explanatory analysis is now presented. The cluster innovation performance model is used to clarify the relationships between cluster innovation performance and various agglomeration and knowledge network factors (see also section 3). The model is estimated for five periods, which were used earlier in this section (see table 5). The model diagnostics suggest that the assumptions of OLS regression are met, and therefore the results are robust (table 7). The results are discussed by sector, beginning with the mature pharmaceuticals and semiconductor sectors.

The agglomeration and knowledge network factors in the pharmaceuticals and semiconductor sectors tend to show statistically significant correlations for a

smaller number of indicators. This result is expected given the mature development phase of these sectors. However, there are some notable correlations which appear related to long-term trends taking place within the sectors, related to the growth of networks in the pharmaceuticals sector, and the consistently high rate of clustering in the semiconductor sector.

The pharmaceutical sector shows a positive and statistically significant influence of knowledge network density (CND), starting in period II (1991-1998), and a negative influence of university government research, starting in period IV (2005-2012). The importance of network factors in cluster innovation performance seems to mirror the growth of knowledge networks in the sector (see figure 7). Taken together with the decline in the clustering rate (see figure 3), it appears that the importance of spatial proximity is gradually being replaced by the growing importance of relational proximity (Boschma 2005).

In a similar way, the negative correlation of the share of university-government research (UGR) with cluster innovation performance mirrors the growth in pharmaceutical patents held by university and government research institutions (see figure 6). The negative correlation can be understood if one considers how universities and corporate research funders tend to collaborate. Many university-owned patents are of lower quality compared to corporate patents, because corporations funding research tend to have the first right to patent. This means that the most commercially promising technologies, although they may be invented at a university, are often owned by corporations (Gautam, Kodama, and Enomoto 2014). A cluster with a large share of university and government-owned patents may therefore have universities and government research institutions that are actively patenting less valuable inventions, which receive fewer citations, and therefore lower the innovation performance of the cluster, as it is being measured in this study.

The semiconductor sector shows a statistically significant influence of knowledge network connectivity (CNC), starting in period III (1999-2004). The connectivity indicator differs from the network density indicator. The connectivity indicator incorporates the transmissivity of knowledge: a researcher who learns from a collaboration with cluster A can transfer that knowledge onward through a collaboration with cluster B. The importance of connectivity coincides with a

growing inter-cluster knowledge network (see figure 7) but also a consistently high clustering rate (see figure 3), suggesting that in the semiconductor sector, clusters function as “hubs” for the combination and generation of new knowledge (Bathelt, Malmberg, and Maskell 2004)

The information technology and solar photovoltaics sectors both undergo a period of rapid growth during the study period (period II, 1991-1998, and period IV, 2005-2012, respectively), and there appear to be consistent influences or correlations before, during and after these growth periods.

Scale-based agglomeration (INV) has a statistically significant negative correlation with cluster innovation performance in both sectors during their high-growth periods, and the negative correlation persists in the information technology sector for the two periods thereafter (1999-2012). It is likely that during the high-growth phase, intensifying competition for talent and resources needed to rapidly grow R&D output, leads to negative economies of scale in clusters.

The two emerging sectors differ in terms of the influence of university-government research (UGR). There is a positive association in the information technology sector before, during and right after the high-growth phase, but a negative association in the photovoltaic sector before the high-growth phase. This suggests that the information technology sector sees positive effects from local university knowledge spillovers or the ability of universities to attract talent (Wolfe 2005; Etzkowitz 2012; Florida 1999). The negative association in the photovoltaic sector could be due to a policy-push towards renewable energy research following the signing of the Kyoto Protocol, as noted earlier in this section. The Kyoto Protocol led to an increase in the number of university and government-owned patents (see figure 6) (Popp, Hascic, and Medhi 2011).

Knowledge networks are strongly associated with cluster innovation performance in the two emerging sectors, with all three network indicators (CND, CNC, IAB) having a positive and statistically significant correlation during the study period. The network influence in information technology appears to be most consistent, although during the high-growth period (II, 1991-1998) and final period (V, 2013-2017) only one network indicator is statistically significant. In the



photovoltaics sector all knowledge network indicators are statistically significant during its high-growth period (IV, 2005-2012).

It is also important to not over-interpret the declining values of the  $\beta$ -coefficients for some of the sectoral indicators, for example for network connectivity (CNC) and network bridging (IAB) in the information technology sector. During the early periods CNC and IAB tend to have low values as there are few clusters. This leads to higher  $\beta$ -coefficients. Furthermore, the innovation performance (IVP, dependent variable) is also higher during the early periods, further raising the  $\beta$ -coefficients (see also figure 4).

The above analysis suggests that, while there are negative economies of scale during the high-growth phase of each emerging sector, there tends to be a positive correlation with one or more knowledge network indicators. It is also notable that network bridging (IAB) is only statistically significant (and positive) in the emerging sectors, suggesting that dominant firms in these sectors influence knowledge flows in ways that benefit the cluster containing their headquarters and main R&D facilities.

Periods	I (1977-1990)	II (1991-1998)	III (1999-2004)	IV (2005-2012)	V (2013-2017)
<b>Agglomeration</b>					
Inventors (INV)					
- Pharmaceuticals	-10.5 (0.684)	-1.57 (0.195)	4.80 (1.10)	6.62 (0.519)	0.507 (1.61)
- Information Tech.	130 (1.18)	-65.4 (4.26)***	-17.3 (4.95)***	-14.5 (2.64)***	0.000230 (0.002)
- Semiconductors	4.89 (0.538)	-0.138 (0.062)	-0.410 (0.652)	-0.331 (0.002)	0.0259 (0.522)
- Photovoltaics	-5.40 (0.038)	-34.9 (0.398)	8.57 (0.287)	-6.31 (2.42)**	-0.164 (0.212)
Univ. gov. res. (UGR)					
- Pharmaceuticals	2.24 (0.176)	0.425 (0.051)	3.26 (0.561)	-3.37 (1.68)*	-1.49 (2.53)**
- Information Tech.	181 (7.29)***	75.0 (2.27)**	99.6 (2.56)**	-16.5 (1.37)	2.94 (0.517)
- Semiconductors	-12.1 (0.546)	-2.67 (0.104)	1.89 (0.120)	-4.42 (1.42)	0.708 (0.462)
- Photovoltaics	-4.35 (0.426)	2.48 (0.198)	-9.38 (1.69)*	1.04 (0.522)	0.886 (1.01)
<b>Networks</b>					
Density (CND)					
- Pharmaceuticals	131 (1.45)	143 (1.67)*	81.0 (1.86)*	27.5 (2.32)**	23.2 (3.91)***
- Information Tech.	23.5 (4.78)***	4.81 (0.269)	11.7 (3.16)***	45.3 (3.30)***	28.1 (0.449)
- Semiconductors	-0.800 (0.009)	6.01 (0.516)	44.4 (0.686)	64.8 (1.59)	26.9 (1.47)
- Photovoltaics	0.968 (0.141)	-4.15 (0.474)	-9.23 (1.02)	14.3 (2.82)***	-3.02 (0.941)
Connectivity (CNC)					
- Pharmaceuticals	26.9 (1.06)	30.6 (0.830)	-19.0 (0.715)	-4.45 (0.543)	0.360 (0.149)
- Information Tech.	35.3 (2.65)***	102 (4.75)***	65.4 (4.54)***	12.0 (2.66)***	0.475 (0.254)
- Semiconductors	-6.95 (0.267)	10.8 (0.471)	22.5 (1.95)*	6.88 (1.65)*	3.13 (2.63)***
- Photovoltaics	0.117 (0.006)	11.7 (1.03)	13.1 (2.01)**	6.92 (1.71)*	1.49 (0.918)
Bridging (IAB)					
- Pharmaceuticals	35.9 (0.626)	-21.2 (0.357)	4.90 (0.137)	-15.3 (1.54)	-3.28 (0.858)
- Information Tech.	170 (3.86)***	42.1 (0.623)	9.53 (0.224)	5.00 (0.403)	11.2 (3.10)***
- Semiconductors	7.40 (0.133)	-12.9 (0.304)	-6.89 (0.368)	8.93 (1.36)	2.15 (0.822)
- Photovoltaics	-26.4 (0.555)	-39.3 (0.457)	-29.4 (1.42)	12.0 (1.71)*	-3.36 (0.149)

Sector Dummy ( $D_{SEC}$ )					
- Pharmaceuticals	4.08 (0.58)	6.59 (0.735)	4.62 (1.13)	3.25 (2.69)***	0.348 (0.812)
- Information Tech.	44.7 (17.6)***	65.7 (12.7)***	28.5 (11.5)***	5.15 (4.14)***	1.68 (4.03)***
- Semiconductors	19.4 (3.14)***	22.7 (4.27)***	12.1 (5.10)***	2.71 (2.50)**	0.267 (0.739)
- Photovoltaics	22.5 (4.27)***	34.5 (7.45)***	18.5 (7.68)***	3.63 (4.41)***	0.855 (2.94)***
USA Dummy ( $D_{USA}$ )					
- Pharmaceuticals	18.7 (3.49)***	10.5 (2.45)**	7.39 (2.91)***	5.48 (4.97)***	1.42 (4.03)***
- Information Tech.	74.1 (3.46)***	96.8 (17.7)***	20.4 (7.59)***	7.29 (8.52)***	2.35 (7.42)***
- Semiconductors	12.5 (2.45)**	15.0 (3.05)***	5.76 (2.34)**	4.59 (4.89)***	1.84 (5.33)***
- Photovoltaics	15.1 (4.04)***	12.8 (2.76)***	22.2 (9.11)***	4.95 (5.52)***	1.39 (3.45)***
<b>Model information</b>					
$n$	2090	901	693	913	541
adjusted $R^2$	0.671	0.865	0.826	0.762	0.745
VIF	1.67	1.98	2.13	2.38	2.38
Breusch-Pagan $p$	$2.2 \times 10^{-16}$	$6.1 \times 10^{-14}$	$5.8 \times 10^{-21}$	$6.77 \times 10^{-8}$	0.00134
Shapiro-Wilk $W, p$	0.74, $2.2 \times 10^{-16}$	0.71, $2.2 \times 10^{-16}$	0.86, $2.2 \times 10^{-16}$	0.84, $2.2 \times 10^{-16}$	0.86, $2.2 \times 10^{-16}$

**Table 7:** Cluster innovation performance model estimation results,  $\beta$ -coefficients with (z-score) and statistical significance at 99% (\*), 95% (\*\*), and 90% (\*) level, unless otherwise indicated.

## 6. CONCLUSION, IMPLICATIONS AND LIMITATIONS

The research results presented in this paper provide an enhanced perspective on the theory of sector and cluster life cycles as it relates to cluster spatial agglomeration, knowledge networks and innovation performance patterns, as well as global shifts. The empirical results generally conform to the assumptions, but they also show that other factors may influence the development of sectors, that mature sectors are influenced by long-term changes, and that there are global shifts in cluster location towards specific countries in Asia.

First, the sectoral development phases are not as distinct as the theory might suggest, making them difficult to define, but perhaps also making it possible to detect sectors that are primed for rapid development in future. For example, in the information technology sector, the initial exploration phase sees an increase in the number of clusters and a gradual rise in patent output. This is followed by a period of high-growth in patent output, after which the sector's growth slows, but knowledge networks continue to expand, and remain influential throughout the three stages just described. Hence, there seems to be a sequence of development: (1) increasing number of clusters, (2) rapid growth in patents and networks, but not in the number of clusters, and (3) slowing growth in the number of clusters and patents, but continued network growth. In this sense there is a pre-growth, growth and post-growth stage of development. Furthermore, agglomeration and knowledge network factors appear to influence cluster innovation performance during the high-growth period, but sometimes also during the pre-growth and post-growth stages. The photovoltaic sector is mostly similar to the information technology sector in this regard, although its development also appears to be influenced by policy-driven research.

Second, mature sectors also undergo changes which appear to be at least partially driven by cluster innovation performance. The mature pharmaceutical sector experienced a rapid increase in knowledge network density and a steady decline in clustering rate during the study period. This suggests that knowledge networks, rather than cluster-based spatial agglomeration, positively influence cluster innovation performance in the sector, and that these factors influence the sector's changing knowledge network and clustering rate.

In contrast, the semiconductor sector has maintained a high clustering rate and a positive correlation with network connectivity. Network connectivity assumes that knowledge is transitive (Wasserman and Faust 1994): cluster A gains knowledge from cluster B in the network, and passes it on to cluster C, creating additional value for cluster C, as it gains knowledge from cluster A and also (some) knowledge from cluster B (with which cluster C is not directly connected). Knowledge transitivity suggests that other actors within the cluster benefit from access to global knowledge networks through local knowledge spillovers. This observation supports the cluster conceptualization of Bathelt et al. (2004), who see a cluster as being connected to global knowledge networks through “pipelines” and also generating local knowledge spillover “buzz” (Bathelt, Malmberg, and Maskell 2004). In the pharmaceuticals sector, it appears that the importance of such local knowledge spillovers have declined, as is evident from the steadily falling clustering rate.

Third, there is a clear shift to Asia in terms of the location of large clusters. This is evident in specific countries, including China, India, Israel, South Korea and Taiwan. The global shifts appear to have accelerated in step with the growth of knowledge networks, a phenomenon that is partly facilitated by advances in communication technology (Dicken 1998; Arkolakis et al. 2018). The trend of specific East Asian clusters “catching up” has been widely noted in other research as well (Kim and Lee 2022; Dutta et al. 2022). National innovation systems are often cited as a factor in the development of East Asian clusters, and are a factor that could be incorporated into future studies.

The research is also limited by the use of patent data as a research and innovation indicator. Patent data is used because it provides a long time series and global coverage, but at the same time it is only a “paper trail” of innovation output (Jaffe, Trajtenberg, and Fogarty 2000), and serves as a proxy measure of a much more complicated process. Nevertheless, patent data can provide global insight into the development of clusters, including at the level of specific sectors and over long time periods, as this study demonstrates.

From a policy and strategic management perspective, the high-growth period is often seen as an opportunity for new firms and clusters to enter a sector, while it poses a risk for incumbents, who may be unable to adapt successfully to sudden

changes in the economic and technological landscape (Lee and Lim 2001; Martin and Sunley 2011). The present research shows that mature sectors also experience notable changes, such as the growth of global knowledge networks and global shifts in the location of top clusters. This suggests that even during a mature phase of development, significant spatial and network changes can and do occur, creating both opportunities and threats for existing high technology clusters. In the United States there appears to be a growing spatial concentration of patenting, which could be driven by growing technological complexity (Balland et al. 2020; Chattergoon and Kerr 2022). However, as shown in this study, which is at a global level, the growth of clusters may be more dynamic and can be influenced by large investments in areas like higher education, whereby universities are able to anchor smaller clusters in certain sectors, such as pharmaceuticals (Wolfe 2005; Chattergoon and Kerr 2022).

## APPENDIX A

List of words or word-parts used to identify universities:

*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, acadadem, 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, tudományegyetem, uceni technick, universt, alumini, suny, ucla, yliopisto, doshisha, insitute of technology, univsers, kaist, szkola, egyetem, univerc, skola, korkeakoulu, universit, instituto superior*

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