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The Global Dynamics of High Technology Cluster Innovation Performance: A Multi-Sector Analysis from 1975 to 2017

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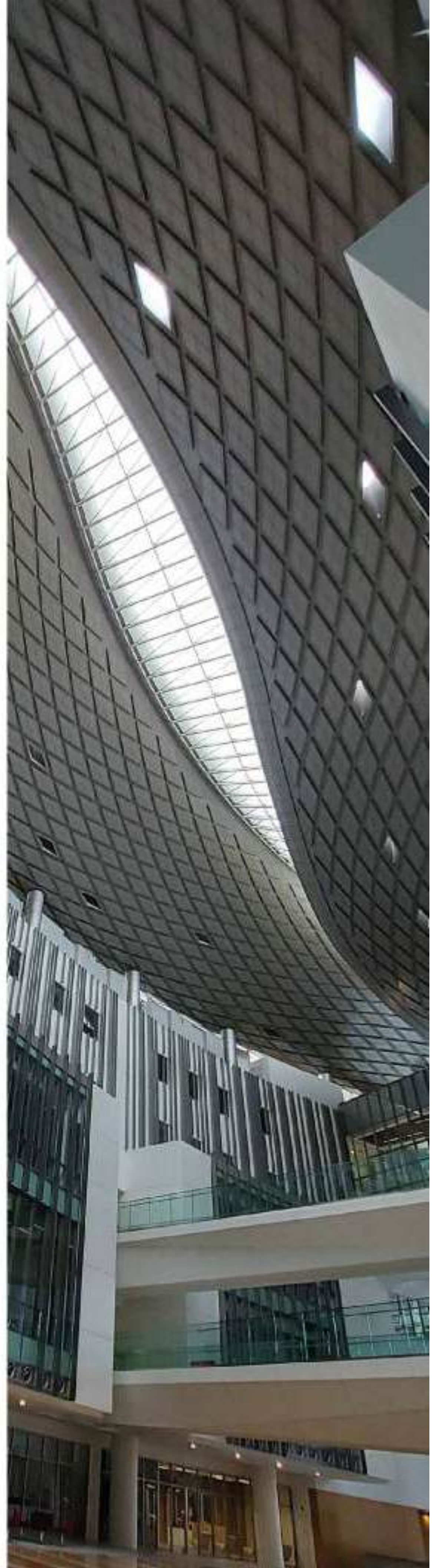

[ABSTRACT / EXECUTIVE SUMMARY]

This research explores the global dynamics of innovation performance in four economically important and patent-rich high technology sectors over a 43-year period, from 1975-2017. The analysis is grounded by sector and cluster life cycle theory and it describes the changes in clusters' innovation performance and explores the varying influence of two important underlying factors: spatial agglomeration and global inter-cluster knowledge networks. The research incorporates two mature sectors, pharmaceuticals and semiconductors, and two sectors which emerged and grew rapidly during the study period: information technology and solar photovoltaics. The empirical results show that global knowledge network linkages are positively associated with cluster innovation performance in all sectors, while cluster size often has a negative effect. The results also show that emerging sectors first experience spatial diffusion, increasing the number of clusters globally. During the high-growth phase, growth takes place primarily in existing clusters. After the high-growth phase the density of the knowledge network continues to increase. There are three main implications for businesses and policy makers. First, knowledge network connectedness is a key factor driving cluster innovation performance, rather than agglomeration. Second, establishing a presence in, or building-up a cluster relatively early, lays the foundations for future growth. Third, global cluster hierarchies are dynamic, suggesting that spatial path-dependence can erode over long time periods, even in mature sectors, in step with global shifts in economic activity, notably the rise of certain Asian economies.

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The Global Dynamics of High Technology Cluster Innovation Performance: A Multi-Sector Analysis from 1975 to 2017

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ABSTRACT

This research explores the global dynamics of innovation performance in four economically important and patent-rich high technology sectors over a 43-year period, from 1975-2017. The analysis is grounded by sector and cluster life cycle theory and it describes the changes in clusters' innovation performance and explores the varying influence of two important underlying factors: spatial agglomeration and global inter-cluster knowledge networks. The research incorporates two mature sectors, pharmaceuticals and semiconductors, and two sectors which emerged and grew rapidly during the study period: information technology and solar photovoltaics. The empirical results show that global knowledge network linkages are positively associated with cluster innovation performance in all sectors, while cluster size often has a negative effect. The results also show that emerging sectors first experience spatial diffusion, increasing the number of clusters globally. During the high-growth phase, growth takes place primarily in existing clusters. After the high-growth phase the density of the knowledge network continues to increase. There are three main implications for businesses and policy makers. First, knowledge network connectedness is a key factor driving cluster innovation performance, rather than agglomeration. Second, establishing a presence in, or building-up a cluster relatively early, lays the foundations for future growth. Third, global cluster hierarchies are dynamic, suggesting that spatial path-dependence can erode over long time periods, even in mature sectors, in step with global shifts in economic activity, notably the rise of certain Asian economies.

Key words: high technology; clusters; knowledge networks; innovation performance; patents

1. INTRODUCTION

The innovation performance of high technology clusters is of great importance for scientific progress, economic well-being, environmental sustainability (Mitchell and Thomas 2017), and geo-strategic competition, such as between China and the United States (Chen, Chen, and Dondeti 2020; Porter 2000). As innovation activity tends to be concentrated in a small number of globally dispersed locations (Feldman and Kogler 2010; Malecki 2021), the growth or decline of a single cluster can have far-reaching implications, both for firms located within the cluster, and for the wider national economies and global value chains connected to them. This makes clusters, and the cities in which they are located, the main spatial unit at which innovation activity takes place (World Economic Forum 2018; Dutta et al. 2022).

The importance of high technology cluster innovation performance requires an understanding of how clusters change over time, and how these changes influence the ability of businesses, research institutes and universities to generate new knowledge. 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).

While there is a rich literature on high technology clusters and the factors associated with innovation performance, much of this knowledge comes from case studies of highly successful clusters or groups of clusters (Saxenian 1996; Asheim and Coenen 2005; Hassink and Shin 2005; Esmaeilpoorarabi, Yigitcanlar, and Guaralda 2018). What appears to be missing is a global perspective on cluster innovation performance which can explain if, and to what extent, conclusions from case studies can be generalized across different sectors, countries, and time periods.

Understanding the factors that influence cluster innovation performance can help firms and other research organizations identify potentially high performing locations for R&D investment. A better understanding of cluster innovation performance can support policy making that targets specific sectors and locations in order to reach economic, scientific, environmental and geo-strategic policy goals.

So far, systematic empirical studies that focus on spatial and temporal variations in the growth and performance of high technology clusters have been lacking, and theoretical work can be seen as contradictory (De Groot, Poot, and Smit 2016). 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 agglomeration (McCann 2013; Richardson 1995).

These variations in innovation performance are 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, view agglomeration advantages as a permanent phenomenon (Porter 2000; Martin and Sunley 2003). In order to shed light on all the stages of the cluster and sector lifecycle, this paper considers the development of high-technology sectors over a period of more than four decades.

The aim of the study is to understand "when" (in terms of sector or development phase) specific factors best explain cluster innovation performance and to also understand the global shifts that have occurred in the location of the top clusters (Dicken 1998). To enable the generalizability of the results, four patent-rich high technology sectors are chosen which have very different technological and socio-technological innovation profiles (Lim 2004; Geels et al. 2017). Semiconductors and pharmaceuticals are considered to be mature sectors, while information technology and solar photovoltaics are seen as emerging sectors.

The study addresses the following research questions:

1. How does innovation performance change over time, including global shifts in the location of top clusters?
2. How do cluster agglomeration and knowledge network characteristics change over time?
3. How does the association between cluster innovation performance and its underlying factors, namely agglomeration and knowledge networks, change over time?

The paper begins with a literature review related to the dynamics and drivers of 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 an overview of research limitation (section 5)

2. LITERATURE REVIEW

This review covers perspectives and theories about innovation performance and how this relates to sectoral and cluster life-cycle models, with the aim of identifying a set of commonalities and assumptions.

High technology clusters can be conceptualized as “locational subsystems” of global (sectoral) innovation systems (Binz and Truffer 2017). The development of individual clusters is therefore connected to the changing economic and technological characteristics of the global sectoral innovation system (Breschi and Malerba 1997). Within this context, cluster innovation performance is 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 growth and innovation performance of a cluster (Capello 2009; Nooteboom 2013; de Vaan, Frenken, and Boschma 2019). Especially in high-technology sectors, which tend to build on a scientific knowledge base, the presence of university and government research institutes are an important source of knowledge spillovers and a magnet that attracts talent to a region (Asheim and Coenen 2005; Davids and Frenken 2018; Florida 1999).

The position of a cluster within global knowledge networks, its network centrality, can be better understood from a social network theory perspective. Having a privileged position within a network confers certain advantages, such as better access to knowledge being produced elsewhere in the network (Wasserman and Faust 1994). The centrality of a cluster within a knowledge network can be defined in different ways.

Centrality can be defined by 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. Transitive influence suggests that cluster A gains knowledge from cluster B in the network, and passes this knowledge on to cluster C. (Cluster C is not connected to cluster A). This creates additional value for cluster C, as it gains knowledge from both cluster A and cluster B.

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).

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.

Although global knowledge networks and local agglomeration 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” (Boschma 2005). 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).

Complementing the systems and agglomeration and network 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 appears to influence the cluster and the sectoral innovation system is presented in table 1, below.

Phase	**Sectoral Innovation System**	**Cluster Dynamics**
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 the 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[1] cluster innovation performance. These expectations are summarized in table 2.

The expectations encompass three development phases (path formation, path creation and path following/renewal) and can be divided into two types: expectations regarding the pattern of *spatial distribution and knowledge network structure* of high technology clusters and expectations about the *influence of underlying agglomeration and knowledge network factors* on the innovation performance of clusters.

The spatial distribution and knowledge network structure are operationalized using 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 in strength: both weak during the path formation phase, strong during path creation, and weak once more during the path following or renewal phase.

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

Table 2: Simplified model of sector and cluster development with expected trends.

[1] "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).

3. DATA, INDICATORS AND RESEARCH MODEL

This section provides an overview of the patenting data, including patent location/geocoding, time aspects and technical corrections (subsection 3.1), the cluster identification process (subsection 3.2) and the cluster innovation model and the measurement of its innovation indicators (subsection 3.3).

3.1 Patent Data

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.[2] 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).

The four research intensive sectors selected in this study 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. Information technology is often regarded as a transformative industry which started to increase productivity and account for a significant share of global patenting globally from the late 1990s onwards (Corrocher, Malerba, and Montobbio 2007). Photovoltaics is often studied as a key renewable energy subsector, and has seen a large increase in patenting starting in the mid-2000s as demand for renewable energy increased (Liu et al. 2011; Leydesdorff et al. 2015; Sampaio et al. 2018). Pharmaceuticals and semiconductors are often studied because both sectors are patent-rich (Dernis et al. 2015). Pharmaceutical research is seen as more science-based, whereas semiconductor research is seen as more applied (and engineering-based), making them useful for sectoral comparisons (Lim 2004).

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

[2] 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.

addresses, these appear to have limited accuracy, especially outside of the United States. Therefore the open source Pelias Geocoder[3] is used to geocode addresses from all countries and territories and all U.S. states with an area of *more than* 20,000 km^2. Countries, territories and states which are smaller than 20,000 km^2 are directly assigned standard coordinates. This approach saves processing time and avoids geocoding errors related to place names. 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 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[4], between 1977-2017, Japanese inventors received 1,268,723 USPTO grants and 362,702 EPO grants (a ratio of 7:2), 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 control variable is included to adjust for the home bias effect.

3.2 Cluster Identification

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.[5] These values give realistic results across 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.

3.3 Cluster Model and Indicators

Cluster innovation performance is estimated using a simple regression model with five

[3] See the official project website at https://pelias.io. Accessed 24 October 2022.

[4] See the OECD Statistics website at https://stats.oecd.org. Accessed 12 November 2022.

[5] 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.

independent variables and two control variables. A control for US clusters (D_{US}) is included to account for the home bias effect (Bacchiocchi and Montobbio 2010) and a sector control (D_{SEC}) is included to account for sectoral differences in citation and inventor patterns. The error term in the models is marked by ε.

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

The model variables are shown in table 4. They are calculated from the patent data belonging to each cluster. Network indicators are calculated using the *igraph* library of R (Csardi and Nepusz 2006).

Indicator	**Unit**	**Measurement definition**
Innovation Performance *(IVP)*	Citations per inventor	***Dependent variable***. 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[6] 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 con-nectivity (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.

[6] Government ownership of patents is indicated in the USPTO database. To identify universities a list of words (or word-parts) is used: *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 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, changes in innovation output and performance are explored (section 4.1). This is followed by an analysis of global shifts (section 4.2) and changes in university-government research and knowledge network structure (section 4.3). Finally, the model estimation results are presented, showing changes in the influence of different factors over time (section 4.4).

4.1 Innovation Output and Clustering

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).

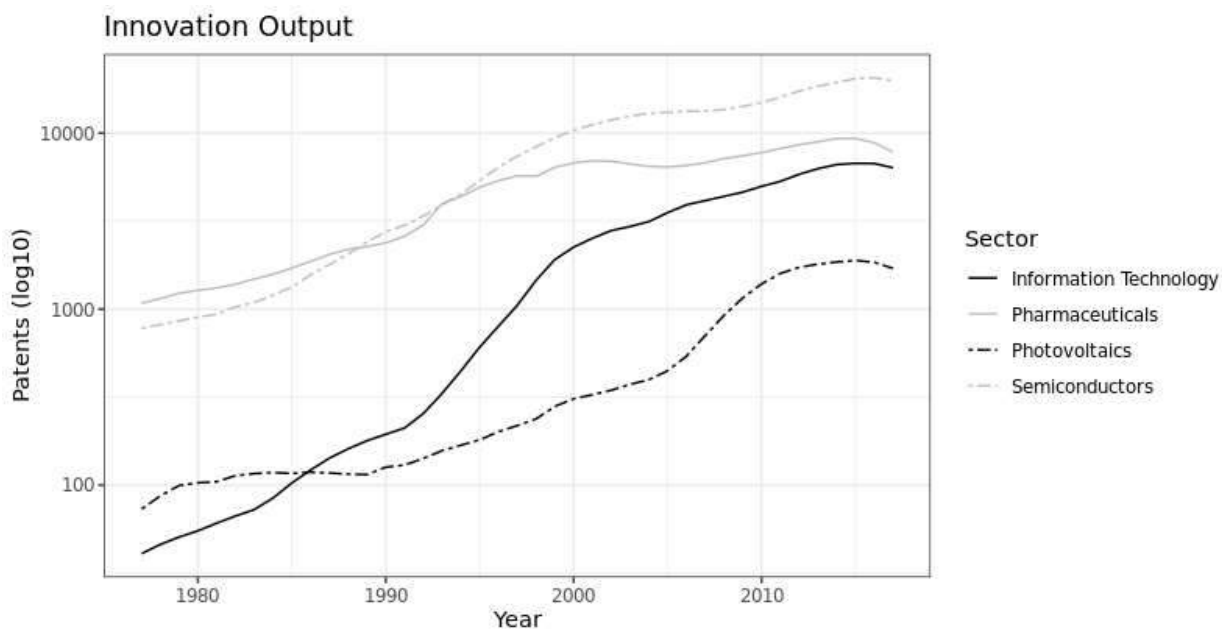

Figure 1: Innovation output (patent grants, five-year moving average).

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

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 ±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, while smaller clusters may lack the critical mass needed to maintain a strong position within global knowledge networks.

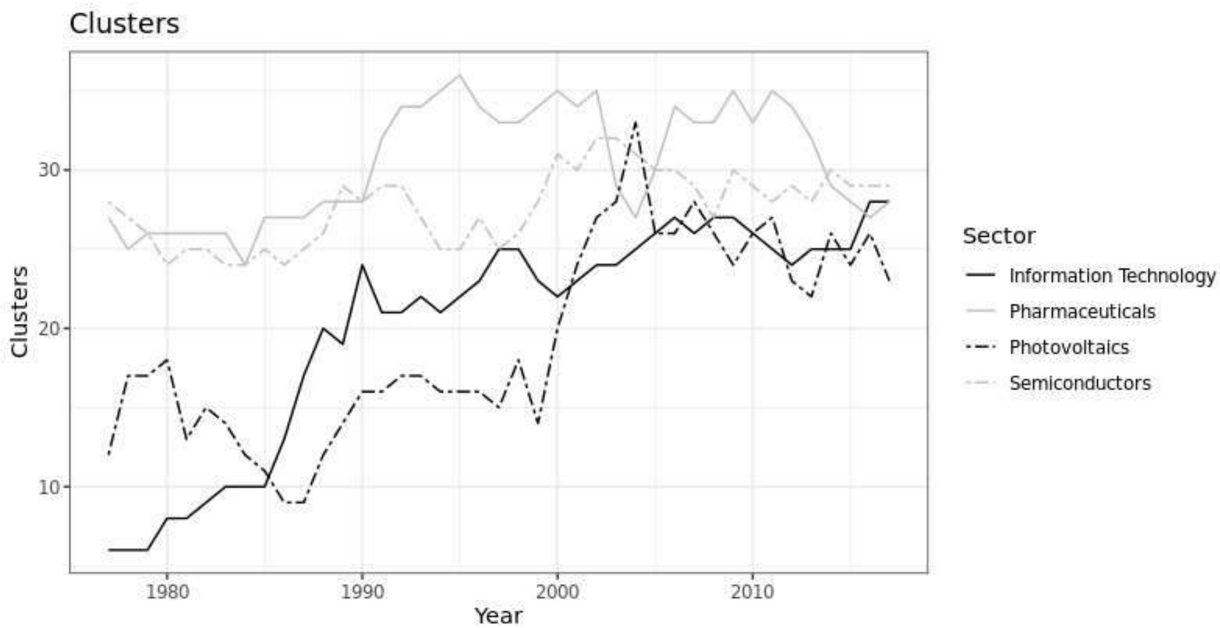

Figure 2: Number of clusters (calculated over moving five-year periods).

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. An increase in the spatial concentration of patenting may also be driven by growing technological complexity, which may be a more significant factor in some sectors (Balland et al. 2020; Chattergoon and Kerr 2022).

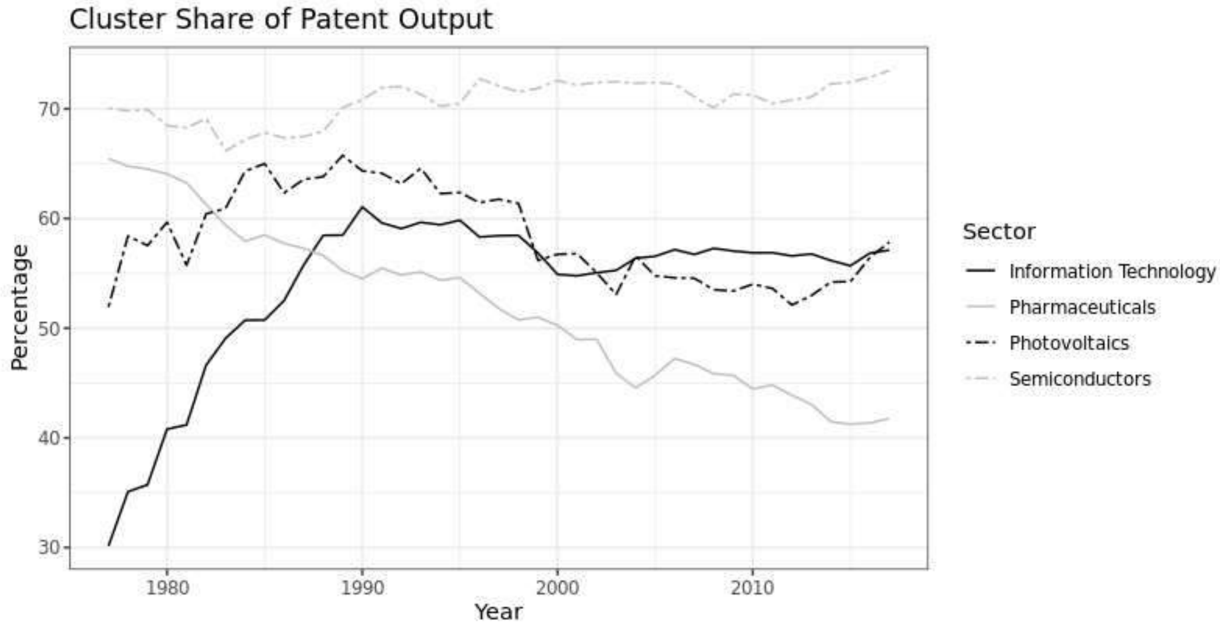

Figure 3: Share of patent output in clusters (clustering rate, calculated over moving five-year periods).

In addition to the growth of innovation output (figure 1), 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 independent of citation lags. All sectors in this study see relatively stable innovation performance until approximately 1995-2000, when a rapid decline begins. This observation appears to 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).

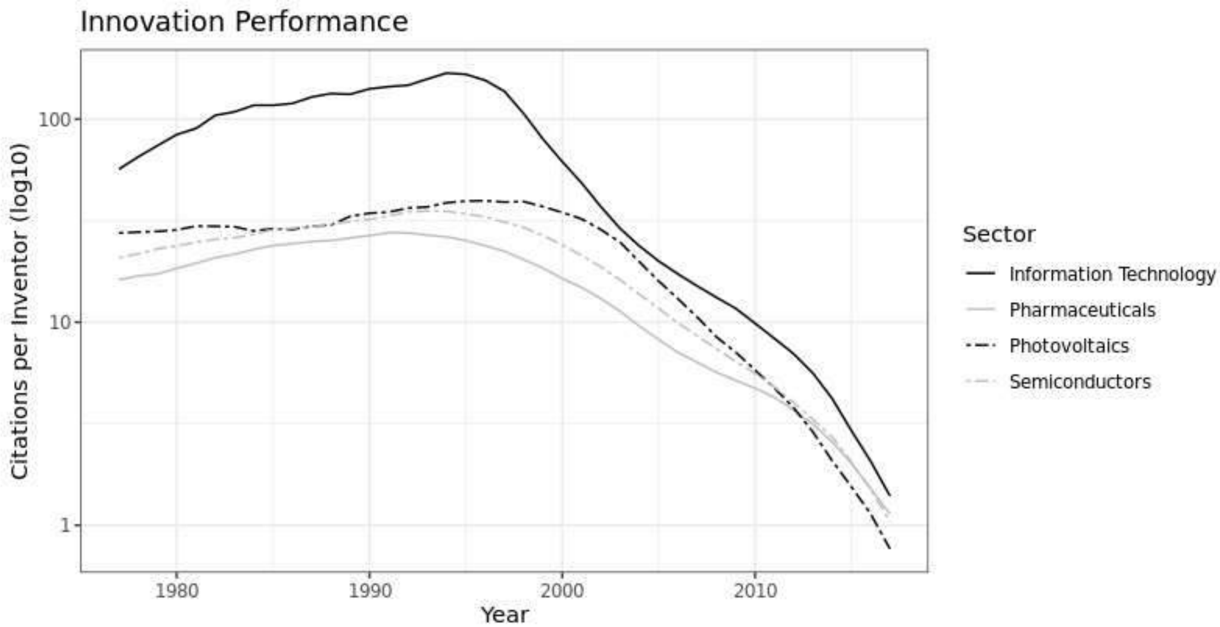

Figure 4: Innovation performance (five-year moving average).

4.2 Global Shifts of Largest Clusters

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) Seoul was not among the top-10 clusters in a single sector. By period V (2013-2017) Seoul is among the top-10 clusters in all four sectors included in this research.

On the other hand, 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 which appear to be the anchor firms of the cluster (Giblin and Ryan 2015). 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. Furthermore, 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 the aforementioned anchor firms, which may also support a large local supplier ecosystem (Giblin and Ryan 2015; Wong and Lee 2022).

In the case of pharmaceuticals, clusters are often anchored around universities (Chattergoon and Kerr 2022). Investments in university research could be related to the emergence of new large pharmaceutical clusters in Seoul and Tel Aviv.

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.

Period	Rank	Information Technology	Semiconductors	Pharmaceuticals	Photovoltaics
I (1977-1990)	1	Tokyo JPN (17)	Tokyo JPN (26)	New York USA (9.0)	Tokyo JPN (20)
	2	Osaka 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 Francisco 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 Francisco USA (7.3)	San Jose USA (6.4)	Tokyo JPN (3.9)	Nagoya 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)	Osaka 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 2 3 4 5 6 7 8 9 10	San Francisco USA (12.8) New York USA (5.7) Tokyo JPN (5.6) Seattle USA (5.1) Los Angeles USA (3.2) Chicago USA (2.5) Boston USA (2.4) Washington USA (1.8) Atlanta USA (1.7) Heidelberg DEU (1.6)	Tokyo JPN (20) Seoul KOR (10) Hsinchu TWN (7.8) San Jose USA (4.8) Osaka JPN (3.9) Nagano JPN (2.6) Gyeonggi KOR (2.5) New York USA (1.9) Singapore SGP (1.6) Nagoya JPN (1.3)	San Francisco USA (4.4) New York USA (4.0) Boston USA (3.9) Tokyo JPN (3.7) Paris FRA (2.2) Basel CHE (1.9) Tel Aviv ISR (1.9) Philadelphia USA (1.7) Osaka JPN (1.6) Seoul KOR (1.5)	Tokyo JPN (11.3) Seoul KOR (8.9) San Jose USA (7.8) Osaka JPN (5.9) Hsinchu TWN (4.1) Frankfurt DEU (2.0) Daejeon KOR (1.4) Boston USA (1.4) Los Angeles USA (1.1) Tsukuba JPN (1.1)
V (2013-2017)	1 2 3 4 5 6 7 8 9 10	San Francisco USA (16) Tokyo JPN (5.1) Seattle USA (4.5) New York USA (3.4) Los Angeles USA (2.9) Seoul KOR (2.3) Boston USA (2.1) Bangalore IND (2.0) Tel Aviv ISR (1.9) Chicago USA (1.8)	Tokyo JPN (15) Seoul KOR (12) Hsinchu TWN (10.6) San Jose USA (4.2) Osaka JPN (3.9) Beijing CHN (3.0) Nagoya JPN (2.1) Albany USA (1.9) New York USA (1.6) Gyeonggi KOR (1.5)	Boston USA (5.2) San Francisco USA (4.4) New York USA (3.7) Tokyo JPN (3.0) Seoul KOR (2.3) Philadelphia USA (1.7) Tel Aviv ISR (1.6) San Diego USA (1.6) Paris FRA (1.5) Basel CHE (1.4)	Seoul KOR (13.2) Tokyo JPN (11.1) San Jose USA (5.5) Osaka JPN (4.4) Daejeon KOR (2.6) Beijing CHN (2.5) Hsinchu TWN (2.2) Frankfurt DEU (1.3) New York USA (1.2) Tel Aviv ISR (1.0)

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

4.3 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.

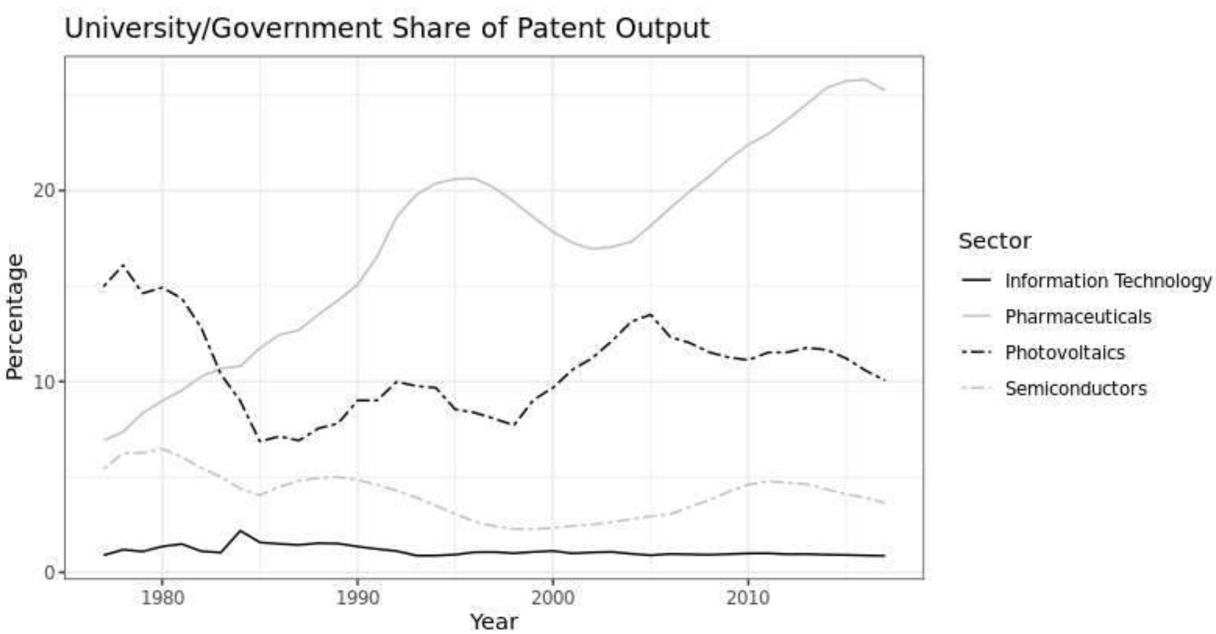

Figure 6: Changes in university-government patenting rate as a percentage of total patenting (calculated over moving five-year periods).

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).

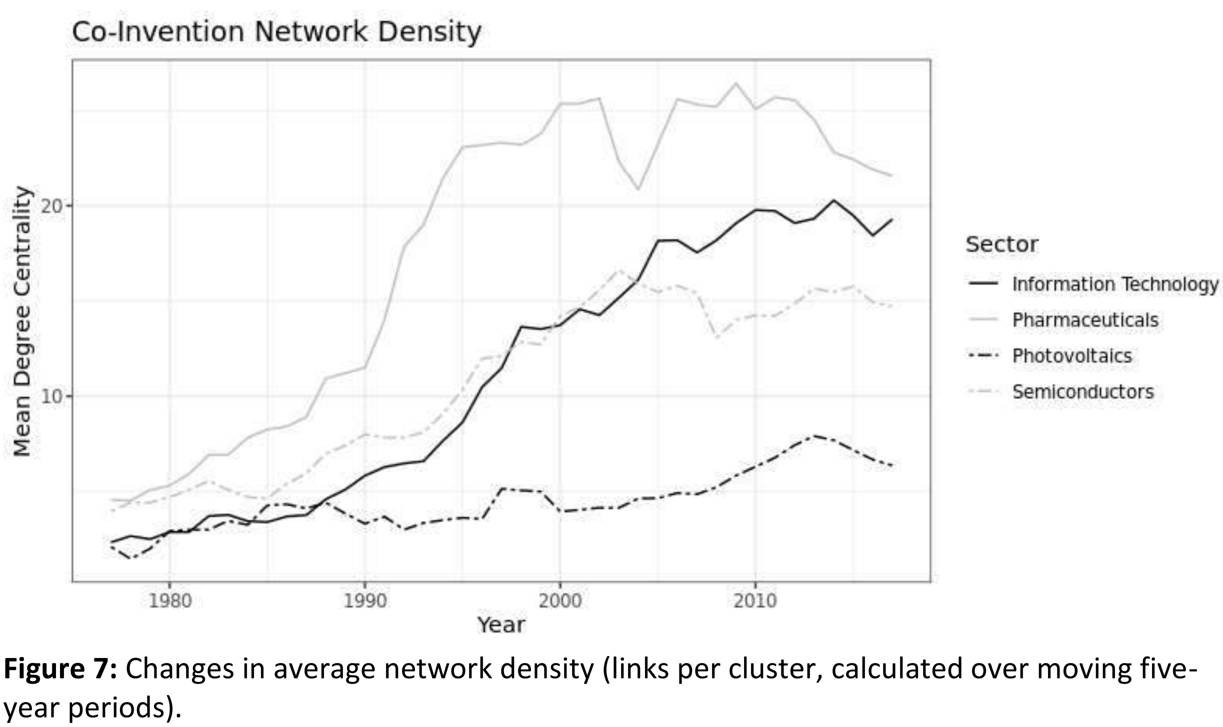

Figure 7: Changes in average network density (links per cluster, calculated over moving five-year periods).

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).[7]

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

[7] It is also important to not over-interpret the declining values of the β-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 β-coefficients. Furthermore, the innovation performance (IVP, dependent variable) is also higher during the early periods, further raising the β-coefficients (see also figure 4).

main R&D facilities.

Periods	**I** (1977-1990)	**II** (1991-1998)	**III** (1999-2004)	**IV** (2005-2012)	**V** (2013-2017)
Agglomeration					
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)
Networks					
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 Control (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 Control (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)***
Model information					
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*	2.2×10^{-16}	6.1×10^{-14}	5.8×10^{-21}	6.77×10^{-8}	0.00134
Shapiro-Wilk W, *p*	0.74, 2.2×10^{-16}	0.71, 2.2×10^{-16}	0.86, 2.2×10^{-16}	0.84, 2.2×10^{-16}	0.86, 2.2×10^{-16}

Table 7: Cluster innovation performance model estimation results, *β*-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 underlying factors influencing cluster innovation performance, on the theory of sector and cluster life cycles, and on the shifting cluster hierarchy.

The results show that the influence of underlying agglomeration and knowledge network factors on cluster innovation performance differ significantly depending on the sector and time period being considered, although knowledge network indicators are always positively associated with innovation performance.

From a temporal and life-cycle perspective, agglomeration and knowledge network factors appear to be more strongly associated with cluster innovation performance during the emerging phase, the high-growth phase and the slower-growth mature phase that follows. During these periods, scale-based agglomeration appears to have a negative influence, whereas the influence of university-government research on innovation performance varies, depending on the sector.

The distinction between life cycle phases also appears to be more fluid than the theory might suggest. Instead, there appear to be an interlinked sequence of development:

- An emerging phase, with an increasing number of clusters,
- High-growth phase, with rapid growth in patents and networks, but not in the number of clusters,
- A mature phase, with slowing growth in the number of clusters and patents, but continued network growth.

While these empirical results generally fit with the existing assumptions about the role of agglomeration and knowledge networks in cluster innovation performance, they also show that the influence of these factors is not the same across all sectors and time periods.

From a sectoral perspective, it is also notable that the mature sectors undergo changes which appear to be at least partially driven by cluster innovation performance. The pharmaceutical sector experienced a rapid increase in knowledge network density and a steady decline in clustering rate during the study period, an observation that is supported by the positive influence of knowledge networks on innovation performance in the sector. By contrast, the semiconductor sector has maintained a high clustering rate and also a positive correlation between innovation performance and network connectivity (eigenvector centrality), which is evidence that clusters are maintained because of the transmissivity of knowledge, generating local “buzz” and knowledge spillovers.

Finally, there is a clear shift to parts of Asia in terms of the location of large clusters. 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 and innovation policies are often cited as a factor in the development of East Asian clusters.

The research also faces other limitations, including the use of patent data as a research and innovation indicator. Patent data is used in this study 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 and specific sectors over long time periods, as this study demonstrates.

The main implications of the research for businesses and policy makers are that a cluster’s knowledge network is closely associated with innovation performance. The influence of networks (positive) and agglomeration (often negative) tend to be stronger during the emerging and high-growth phase of the sector, while the growth rates of individual clusters vary due to broader economic and policy influences. An exploration of the policies and broader economic factors that support cluster growth could be incorporated into future studies.

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