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Multi-scalar Networks and Urban Context in Invention Performance of Photovoltaic Clusters

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1.A ‘GLOCAL’ PERSPECTIVE

Solar photovoltaics PV are expected to contribute to the reduction of greenhouse gas emissions and the diversification of energy supply (Breyer et al. 2013; IEA 2016). It is therefore not surprising that the invention performance of the sector which encompasses e.g. micro/nano electronics, materials science and optics, has been the subject of significant attention, both in the academic community and among policy makers. Academic research has generally focused on the photovoltaic sector in one country or a small number of countries in the context of industrial policy, international technology transfer and international competition (de la Tour et al. 2011; Grau et al. 2012; Vidican et al. 2012; Klitkou and Godoe 2013; Lo et al. 2013; Wu 2014; Zheng and Kammen 2014; Kim and Kim 2015). These studies are mainly at the country level and sometimes contain a comparison between a few countries. There are also various studies of specific photovoltaic industry *clusters* (or cities/regions) in a country which address similar aspects (Klitkou and Coenen 2013; Luo et al. 2013; West 2014; Dewald and Fromhold-Eisebith 2015). And there is a small number of studies which explore the size, growth and geographic distribution of research output in the photovoltaic sector based on data sets that are global in coverage (Breyer et al. 2013; Leydesdorff et al. 2014).

This study provides a ‘glocal’ perspective on innovation, by identifying regional photovoltaic clusters around the world, and by linking the influence of agglomeration factors (e.g. local knowledge networks) and global knowledge networks as well as specific regional circumstances to the invention performance of these photovoltaic clusters. The positioning of the research lens is at the intersection of global and urban/regional factors, thereby addressing multi-scalarity, and offers an original contribution to research on photovoltaics research clusters. The global factors considered are global knowledge networks: networks of personal and institutional relationships that enable the transfer of knowledge on a global scale. Examples include the global research collaboration network (De Prato and Nepelski 2014) and the global academic weblinks network (Barnett et al. 2014). Other salient examples include the cross-border knowledge transfers that take place within multinational corporations (MNCs) which are enabled by MNCs private networks of branch laboratories located in industry clusters worldwide (Castellani et al. 2013).

While it is clear that international research activities are rapidly growing, especially in terms of their global distribution and importance of global knowledge networks (Audretsch et al. 2014; Locke and Wellhausen 2014), there are also indications that internationalization may weaken or limit the development of internal knowledge networks (Kwon et al. 2012; Van Geenhuizen and Nijkamp 2012; Ye et al. 2013) and hinder the invention performance of some knowledge intensive industries (Stek and van Geenhuizen 2015). In fact the question is to what extent the agglomeration factor as physical proximity (local spillovers) has remained important or is strongly complemented with relation proximity in long-distance networking in which different power realities between the research partners may emerge. The influence of long-distance knowledge networks on the invention performance of industry clusters therefore remains unclear, and the photovoltaics sector is no exception.

To address this knowledge gap, a quantitative model is developed that enables to assess the influence of multiple knowledge networks and urban/regional factors on the invention performance of PV research clusters, for the years 1990-2011. The multi-scalar approach is based on emerging theories about the role of spatial and relational proximity in innovation and a multidimensional understanding of knowledge networks as consisting of different types of relationship. In this paper the personal co-invention network, which is often embedded within institutional collaboration networks (Dodgson 1992) and the relevance of collaboration outside the cluster are also analyzed. Together these networks provide a differentiated perspective on relational proximity.

The paper makes a theoretical contribution to the understanding of inventive performance in industry clusters. This contribution consists of exploring how the physical proximity factor (agglomeration) and the relational proximity (long-distance networks) factor influence spatially concentrated knowledge creation in industry clusters, including the possibility of knowledge flows mainly in one direction, which might raise the invention performance of the receiving industry cluster at the expense of the sending cluster. The paper also makes a methodological contribution by using mainly bibliographic data to extract invention indicators, combining spatial analysis and scientometric network analysis approaches. This combination enables the identification of industry clusters, the extraction of cluster invention input and output indicators and the construction of multiple inter-cluster knowledge networks from which network indicators are calculated.

The paper is centered on the following research questions: First, what is the global distribution of inventive activity in the photovoltaic sector, which clusters are dominant in terms of size, and how have clusters developed during the study period? Secondly, how do agglomeration factors and knowledge network factors influence the invention performance of clusters in the photovoltaic sector, among other factors? First, the current literature is briefly addressed, which forms the basis for the research model (section 2). This is followed by a description of the data and methodology (section 3). Next is a discussion of the empirical outcomes of the study, the changing global distribution of inventive activity (section 4) and the results of exploration of the research model (section 5). The paper closes with conclusions and implications, and tentative research paths for the future (section 6).

2. THEORETICAL BACKGROUND

2.1 Spatial and relational proximity

The influence of spatial proximity on invention performance under the label of agglomeration economies, has been studied theoretically and empirically for decades, inspired by scholars such as Marshall and Jacobs (Capello 2009). Despite a controversy between ideas on specialization-based advantages (Marshall 1920) compared to diversity-based advantages (Jacobs 1970), agglomeration advantages can be discussed using three main dimensions. The first dimension of these localized advantages relates to being spatially close in larger cities or clusters, including lower transport and transmission costs, proximity to final markets or test/launching markets, a larger chance for meeting of two agents, eventually leading to serendipity, and easier exchange of creative ideas (Morgan 2004). The second dimension puts an emphasis on productivity increases due to cost reductions (scale effect) and localized accumulation of production skills. A third dimension draws attention to synergy and refers to the rise of a set of common values and beliefs which acts as the rationale for the reduction of transaction costs (Williamson 1981). In so-far the advantages deal with knowledge, the appropriate concept is localized knowledge spillovers, and invention and innovative activity at universities, research institutes and companies in cities or clusters are regarded to benefit from them (Jaffe 1989; Acs et al. 1994; Audretsch and Feldman 1996; Anselin et al. 1997; Autant-Bernard 2001). However, various doubt have been cast on the condition of spatial proximity in productive inter-organizational learning, summarized in the assumption that spatial proximity is neither a necessary nor a sufficient condition for creative learning and invention (Boschma 2005; Karlsson 2010; D'Este et al. 2012).

The idea that 'advantages of spatial proximity' also work on a distance and in a similar manner compared to the ones that are localized, has emerged since the early 2000s and has been increasingly elaborated ever since (Ertur and Koch 2011). Thus, Breschi and Lissoni (2001) argue that collaborative networks are channels for knowledge spillovers that are not limited to local environments, instead, they can span long physical distances (Maggioni et al. 2007; Ponds et al. 2007; Maggioni and Uberti 2009). According to this line of thinking, the study of regional invention and innovation has shifted from a focus on close territorial relationships towards an emphasis on collaboration that increasingly occurs between cities or clusters as widely spread network-based systems through which knowledge circulates and is enriched, which is enabled by complementary needs and common values and culture of network partners (Cohendet and Amin 2006). Often such a situation has been viewed as merely positive in enhancing innovation in clusters. Particularly in high-tech sectors, research collaboration through long-distance networks has been regarded as crucial for corporate inventive performance, like in the biotechnology industry (Gertler and Levitte 2005; Cooke 2007). What however might occur, if local firms are strongly collaborating with Multinational Corporations (MNCs) from elsewhere or if they are established or acquired by such companies, is that these local firms develop knowledge strategies depending on their role and the power distribution in the production organization within the (parent) MNC (Van Geenhuizen and Nijkamp 2012; Hervas-Oliver and Albors-Garrigos 2013). Particularly, the role of producing knowledge for the MNC means that MNCs elsewhere learn from their foreign subsidiaries, which is named ‘reverse’ knowledge transfer and which may cause a cluster to weaken instead of grow due to global interaction (Frost 2001; Frost and Zhou 2005; Ambos et al. 2006; Castellani et al. 2013; Awate et al. 2014).

Firms within a cluster can leverage their relationships with partners inside and outside of the cluster. In smaller clusters which lack the local networking advantages of agglomeration economies, it is likely that knowledge relations with partners outside of the cluster play a more prominent role (Tödtling and Trippl 2005). At the same time, the strong relational proximity of a cluster to other clusters may be strengthening the spatial agglomeration effect, as large clusters tend to be important nodes in national and global knowledge networks (Bathelt et al. 2004), for example in biotechnology (Huallacháin and Lee 2014). However, as the example of knowledge relations within MNCs indicates, the type of knowledge and the type of knowledge relationship also influence a cluster's invention performance.

Patterns of knowledge relations may also vary depending on the industry sectors (Iammarino and McCann 2006; Jensen et al. 2007) and the diversity involved, the knowledge resource base such as R&D budgets and the social capital of the region in question (Tödtling and Trippl 2005; Masciarelli et al. 2010). The last involves among others the type of collaboration, and the local benefits and excellence created by spanning boundaries and synergy, such as between universities, government and industry as in the Triple Helix network, could make a difference in invention performance (Etzkowitz and Leydesdorff 2000; Ranga and Etzkowitz 2011; Taheri and van Geenhuizen 2016). The previous discussion suggests that a plurality of relations and networks co-exist which may influence invention performance in different ways which will be tackled in this paper.

2.2 Incorporating network characteristics into an invention performance model

In some literature, quantitative invention or innovation performance models have been reduced to a knowledge production function in which the influence of a small number of factors is studied. This approach has led to insights such as: the institutional and policy factors that influence national innovation performance (de Rassenfosse and van Pottelsberghe de la Potterie 2009; Furman et al. 2013), the importance of the geographic distribution of university-industry knowledge spillovers within a country (Ponds et al. 2010), the importance of local absorptive capacity in terms of human capital (Charlot et al. 2014) and the importance of formal research collaboration within clusters to explain cluster invention or innovation performance (Fritsch 2004). Thus, although the knowledge production function typically represents a simplification, it can be considered as a well-accepted modeling approach.

Building on the theoretical understanding of agglomeration economies and global networks, as well as regional qualities and invention performance, a simplified conceptual model is proposed: agglomeration and networks factors as well as regional research and innovation qualities are conceived as the factors that influence inventive performance. The primary elements of a knowledge production function are knowledge input factors and knowledge output factors (Romer 1990; Jones 1995). In this paper, the number of inventors (a proxy for the total number of researchers) per cluster is the main model input and a compound indicator of inventive performance is the model output. Dividing input by output yields an indicator of the 'productivity' of the cluster: the inventive performance.

>>Insert Figure 1 (simplified conceptual)

3. DATA AND METHODOLOGY

First, the increase of inventive performance in the photovoltaic (PV) sector will be showed, on the basis of global patent applications (Figure 2). In the second half of the 1990s and since approximately 2003 an acceleration of growth has taken place in photovoltaic inventive activity, of which the last has continued over time. After 2011, there are no more data available due to the time needed for patent applications to enter the database. Specific periods that are of significant interest in this study are the period prior to rapid growth (1998-2000), the period right after a high-growth trajectory has established itself (2004-2006) and the most recent three-year period for which data is available, which marks approximately one decade since the PV sector commenced its high growth trajectory (2009-2011). These three periods are the points at which the spatial distribution of inventive clusters is observed. The final period is further explored using regression analysis.

>>Insert Figure 2

This study is based mainly on bibliographic sources (patents and scientific publications) which enable the observation of changes over longer time periods, while offering global coverage of units (universities, companies) in local clusters by exploiting the address information contained in the bibliographic sources. These bibliographic sources form a 'paper trail' of innovation activity (Jaffe et al. 1993), data from which we use. On the one hand, the use of bibliometric data as invention or innovation indicators has disadvantages, including variations in patenting propensity between sectors (Kleinknecht et al. 2002). On the other hand, bibliometric indicators such as patent counts and citation counts seem like valid indicators in high-technology industries and tend to show close statistical overlap with other innovation indicators such as R&D inputs and new product announcements, which are also used in the literature to measure innovation performance (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004).

In this study, bibliometric data is obtained from two sources. Patent data is obtained from the Spring 2015 edition of the Patent Statistical Database (PATSTAT), which is published every 6 months by the European Patent Office (EPO) and contains data from all major patent offices, and scientific publications are downloaded from the *Scopus*® database, which is maintained by Elsevier, as academic publisher. All data processing is carried out using *R* (R Core Team 2015). Further, *rvest* (Wickham 2015) is used to communicate with the *Scopus* Application Programming Interface (API). *RMySQL*

(Ooms et al. 2015) is used to communicate with and populate a MySQL database of bibliographic data.

For the delineation of the technological domain, PV sector, this study uses the new Y02E cooperative patent classification (CPC) from the full (USPTO) and the European Patent Office (EPO), which contains renewable energy technologies, including a subcategory for photovoltaics (Y02E/5) and hybrid thermal and photovoltaic technologies (Y02E/6). With regard to scientific publications, the author is not aware of a similar classification, and therefore relies on the advanced search option in *Scopus*, where all documents (both conference proceedings and journal publications) with abstracts that contain the phrases ‘photovoltaic cell’ or ‘solar cell’ and which fall within the *Scopus*-designated subject areas of chemical engineering, chemistry, computers, earth science, energy, engineering, materials, mathematics or physics, can be found.

Clusters in this paper are conceived as “geographic concentrations of industries related by knowledge, skills, inputs, demand, and/or other linkages” (Delgado et al. 2016). Accordingly, geographic concentration is used to identify clusters. Both of these measures are extracted from patent data because the focus is on invention performance, which is primarily reflected in patent output (Jaffe et al. 1993; Hagedoorn and Cloodt 2003). Concentration refers to the intensity of patent output in geographic space based on the stated place of residence of inventors. Because patents can be assigned to organizations far away from where the actual invention activity took place, inventor locations are the more reliable geographic indicator of invention activity. To geographically locate patents (and scientific publications) the (partial) addresses of the affiliated institutions (including assignees) and addresses of inventors are used. These addresses can be geo-located using mapping applications, in this case we use TwoFishes, an open source geocoder. This approach has been used previously with a smaller data set and different geocoders (Leydesdorff and Persson 2010; Leydesdorff et al. 2014). By using this mapping application, the success rate of geo-locating addresses is about 90 per cent. The geo-location of addresses allows the locations of inventors to be plotted on a map and clusters are identified by using the standard ‘heat map’ algorithm, formally known as kernel density estimation (Rosenblatt 1956; Parzen 1962). In this study a standard quartic (biweight) kernel shape is used with a radius of 20 km. Areas with the 95 per cent highest concentrations are designated as cluster-cores, and a radius of again 20 km is drawn around these cores to designate the area of concentration, which is the first step in identifying a cluster. The 20 km radius is based on a previous study (Alcácer and Zhao 2013), an analysis of commuting distances and robustness checks which show that a larger than 20 km radius tends to create ‘mega clusters’ which for example, include large parts of Belgium, Luxemburg, Germany, France and Switzerland in a single mega cluster. In the final 2009-2011 period 109 clusters were available and this period is taken as the subject of regression analysis. Clusters are named after the largest urban population center inside the cluster. Therefore Silicon Valley is in the San Jose-cluster and all of north-eastern Taiwan is in the Taipei-cluster, while southern Taiwan is in the Kaohsiung-cluster.

The indicators used in the regression modeling are summarized in Table 1. The unit of analysis is the cluster and bibliometric data on the indicators have been gathered for 2009-2011, which are the most recent years of continued growth. A further explanation is given in next part of this section.

Table 1 Model indicators, measurement and descriptive statistics

Indicator	**Description**	**Measurement Unit**	**Minimum**	**Mean**	**Maximum**
INVP	Inventive performance	Composite indicator	2.51	5.4	9.47
INVT	Cluster size	No. of inventors (log)	2.32	4.73	8.61
$INVT^2$	Cluster size, squared	No. of $inventors^2$ /100,000	0	8.23	299.83
PROX	Weighted proximity to other large clusters	Composite indicator	0	6.32	9.27
INVS	Co-invention network diversity	No. of connected clusters (log)	0	1.83	3.95
SCIS	Co-authorship network diversity	No. of connected clusters(log)	0	0.35	2.2
INVW	Internal collaboration rate	**C**onnections per patent (log)	0	2.87	6.89
NISQ	National innovation system quality	Composite indicator	3.1	5.09	5.77
TEIL	Regional high-technology diversity	Composite indicator	0.74	1.78	1.99
SCIE	Regional related scientific output	No. of papers (log)	0	2.74	6.34
RERE	Regional research expenditure	USD billion (log)	-1.6	5.65	11.02

Below is a discussion in more detail of the indicators used, agglomeration, network and regional quality factors, this includes motivation for using them and their calculation (approximation).

- Inventive Performance (INVP) is a composite indicator obtained by multiplying the number of in-bound patent citations by the number of patent applications from the cluster, divided by the total number of patent families. Whenever a patent generated by inventors in the cluster is cited by another patent, this generates an in-bound patent citation for the cluster. Research suggests that the number of citations a patent receives is a proxy for its value (Hagedoorn and Cloodt 2003; Lanjouw and Schankerman 2004; Squicciarini et al. 2013; Lee 2016).

- Number of Inventors (INVT)**.** The size of a cluster is measured by the number of inventors, as an approximation for the number of researchers, as the basic measure of cluster input (Rassenfosse and van Pottelsberghe de la Potterie 2009; Egeraat et al. 2015). From patent data the number of unique inventors active in a cluster in a specific period of time can be measured and has a high correlation with the number of researchers (Stek and van Geenhuizen 2015).
- Proximity to Other Clusters (PROX)**.** This is calculated based on the sum of a distance weighting coefficient and the number of inventors in the other cluster (s) (INVT). The distance weighting coefficient is between 0 (for clusters at a distance of 250 km or more) and 1. At a distance between 0 to 250 km, PROX = INVT x $(-(DIST/250)^2 + 1)$, where DIST is the distance between clusters.
- Patent Co-Invention Network Size (INVS)**.** The size of the patent co-inventor network can be (more) precisely formulated as the simple degree centrality of a cluster (node) in the inter-cluster patent co-invention network. Degree centrality is the number of links that a node has with nodes in the network (Wasserman and Faust 1994). The simple degree centrality is a measure of the number of unique nodes. Being connected to many different nodes, may give access to a greater diversity of knowledge.
- Share of Internally Invented Patents (INVW) — See previous indicator. INVW is partly calculated based on the *weighted* degree centrality of the node of interest in the patent co-invention network. The weighted degree centrality is the total number of links to other nodes in the network. The degree centrality is divided by the total number of patents in the cluster, and then subtracted from 1 (a situation in which all patents in the cluster are co-invented). This yields a measure of the percentage of patents that are invented without collaboration with other clusters. A very high number of co-invented patents tends to coincide with a cluster's dependency on other clusters, which may eventually lead to 'reverse' knowledge flows.
- Scientific Co-Authorship Network Size (SCIS) – Also, see the previous indicator. SCIS is the simple degree centrality of a node (cluster) in the inter-cluster scientific publication co-authorship network.
- National Innovation System Quality (NISQ)**.** The NISQ score is derived from the Global Competitiveness Report published annually by the World Economic Forum. It is based on the 12th pillar (Innovation) score in the Global Competitiveness Index. As it is an indicator at national scale, it does not vary between clusters located in the same country.
- Regional High Technology Sectoral Diversity (TEIL). Previous research is ambiguous about the importance of greater technological diversity in cities or regions on innovation. Some have suggested that it is positive (Feldman and Audretsch 1999), while others have found no or a negative relationship (Leslie and Huallach'ain 2007) which suggests technological specialization benefits industry inventiveness. To calculate technological diversity the Theil index is used (Theil 1967) where the index components are the relative share of medium-high and high technology ISIC/NACE sectors in a cluster compared to the global average share of that ISIC/NACE sector at the two-digit or three-digit (for electronics) code level. Calculations are performed using the *ineq* package in R (Zeileis 2014), and the Theil index is subtracted

from the maximum value (the cluster with the least diversity) to obtain high values for high-diversity clusters. The sector diversity in the clusters is estimated by geocoding all patents of all sectors and then carrying out the calculation based on those patents located within the geographical boundaries of the cluster.

- Regional Cluster-related Scientific Activity (SCIE)**.** The total number of scientific publications that are relevant to the sector (weighed by relative contribution in case of multiple authors) with affiliations located within the cluster. This indicator reflects local scientific excellence in a way.
- Regional Research Expenditure (RERE)**.** Studies suggest that the research intensity of a cluster or region has a positive impact on overall inventive output (Leslie and Huallach´ain 2007; Charlot et al. 2014). Unfortunately research expenditure statistics for city-regions are not readily found. However Business Expenditure on Research and Development (BERD) is correlated to patent output in medium-high and high technology sectors, especially if a correction is made for the patenting propensity of different sectors. Therefore, national data of BERD expenditure can be linked to national patent data, allowing patent data of different industries to be used as a proxy for research expenditure in a city or region. By geocoding all patents, as described for TEIL above, each patent can be linked to a US$-amount of research expenditure. This allows a total value of regional BERD to be estimated.

4. CHANGING GLOBAL DISTRIBUTION OF PV CLUSTERS

While globally distributed, the inventive activity of the photovoltaic sector is concentrated in a relatively small number of urban areas in Western Europe, East Asia and North America with only a few clusters located outside of those regions. These clusters have not been the same over the total observation period: clusters in the top, except for the top four, Tokyo, Osaka, San Jose, do shift in position. Table 2 shows 1998-2000 as the first acceleration that came to an end, 2004-2006 as the start of the second acceleration and 2009-2011 as years of continued strong growth. The shifts are visible in the start of the second acceleration with the rise of Seoul and Taipei, and to a smaller extent Daejeon, and the relative decline of American cities like Los Angeles, New York and Boston, compared to the first acceleration.

Among the European cities, Frankfurt has kept a stable position (rank 6), but some other cities were not able to keep their position in the top-15, like Stuttgart, Lausanne and Düsseldorf, after the first acceleration. The question arises, as to what makes clusters emerge or disappear from the list of largest global invention in PV technology, in other words what influences their inventive performance?

Table 2 Top 15 clusters according to inventive performance

1998-2000 **1st acceleration**	**2004-2006** **Start 2nd acceleration**	**2009-2011** **Sustained strong growth**
Tokyo	Tokyo	Tokyo
Osaka	Osaka	Osaka
Los Angeles	San Jose	San Jose
San Jose	Seoul	Taipei
New York	Taipei	Seoul
Frankfurt	Frankfurt	Frankfurt
Boston	Albany	Daejeon
Albuquerque	Los Angeles	New York
Denver	New York	Los Angeles
Stuttgart	Boston	Boston
Sydney	Detroit	Detroit
Lausanne	Daejeon	Albany
Detroit	Freiburg	Denver
Fukuoka	Eindhoven	Jerusalem
Düsseldorf	Paris	Freiburg

5. FACTORS INFLUENCING PV INVENTIVE PERFORMANCE

A stepwise analysis is followed, by separately inserting agglomeration variables, network variables, agglomeration-network interaction and regional innovation/research variables into the model, before the full model is estimated (Table 3). In terms of 'power' of the various factors, the results indicate a relatively strong influence of agglomeration factors and network factors, and a weaker influence of regional research/innovation qualities, as evidenced by the adjusted R^2 of 0.67 (Model A), 0.62 (Model B) and 0.42 (Model E) respectively. Thus, where it comes to importance of agglomeration versus relational economies, the results indicate approximately an equally strong influence, given the indicators used. In particular, the beta-coefficient of cluster size (inventors) (INVT) and the beta-coefficients of size of the external co-inventor networks (INVS) and relative importance of these networks (INVW) suggest a positive and significant influence on inventive performance. With regard to regional characteristics, the beta-coefficients of quality of the National Innovation System (NISQ) and excellence in regional scientific activity in PV (SCIE) also indicate positive and significant influence on inventive performance of clusters. By considering the full model (Model F), the picture remains the same, except for disappearance of influence from regional excellence in scientific activity and appearance of research expenditure in the region (RERE) of which the beta-coefficient is, however, negative. As the last indicator reflects expenditure in all patent sectors, a slight interaction with size of the cluster may cause this result, although PV research is only a small part of total research activity. In addition, the years 2009-2011 represent strong growth in PV patent output, which could mean that at this level of growth, regional expenditures could cause phenomena of expenditure saturation and stress in the inventor communities due to competition for talent between PV and other sectors.

Table 3 Results of regression analysis of inventive performance (2009-2011)

	A	**B**	**C**	**D**
	ß coefficient (s.e.)	**ß coefficient (s.e.)**	**ß coefficient (s.e.)**	**ß coefficient (s.e.)**
INVT	0.90 (0.08)***		0.56 (0.11)***	
INVT^2	0.002 (0.002)		0.003 (0.002)	
INVT·INVS				0.16 (0.01)***
PROX	0.02 (0.03)		0.03 (0.03)	
INVS		1.02 (0.09)***	0.54 (0.11)***	
SCIS		0.20 (0.14)	-0.09 (0.13)	
INVW		0.72 (0.08)***	0.36 (0.09)***	
NISQ				
TEIL				
SCIE				
RERE				
Constant	1.00 (0.41)**	1.40 (0.33)***	0.54 (0.41)	3.90 (0.15)***
n	109	109	109	109
Adj. R^2	0.67	0.62	0.73	0.58
VIF	1.43	1.16	2.01	-n.a.-

	E ß coefficient (s.e.)	**F ß coefficient (s.e.)**
INVT		0.67 (0.10)***
INVT^2		
INVT·INVS		
PROX		0.002 (0.029)
INVS		0.48 (0.13)***
SCIS		0.04 (0.13)
INVW		0.36 (0.09)***
NISQ	1.05 (0.16)***	0.36 (0.13)***
TEIL	-0.06 (0.42)	0.07 (0.27)
SCIE	0.36 (0.08)***	-0.06 (0.07)
RERE	0.08 (0.05)	-0.07 (0.04)*
Constant	-1.33 (1.06)	-1.12 (0.73)
n	109	109
Adj. R^2	0.42	0.77
VIF	1.19	2.17

Remarkably, our results indicate the absence of curvilinear influence of the size of the cluster, pointing to ‘constantly increasing returns’, but also absence of influence of proximity of a cluster to adjacent clusters, indicating absence of spill-over effects from proximate clusters.

Finally, the beta-coefficient of interaction between cluster size and size of the network has a positive influence on inventive performance and produces a model power alone of 0.58 (model D). This could indicate that various combinations of large and small clusters with large and small networks, work out positively. Figure 3 shows how the best performing clusters in 2009-2011 are positioned on the axes of these two factors. The five best performing clusters have all a high score on cluster size, while four of them have also a high score on network size: San Jose, Tokyo, Osaka and Seoul. Next largest clusters, Frankfurt, New York, Los Angeles, Boston and Detroit (all outside Asia) face the combination of a medium-sized cluster with large network size. Researchers in these clusters seem to compensate disadvantages of a somewhat smaller cluster size with a relatively large network. Cultural factors could explain this situation, with researchers fluently (in English) connecting outside the cluster in US and Europe, but also longer traditions of networking. However, the strong external networking in the American clusters could not prevent their fall to a lower position on the top, which may be indicative more of lower increases in research expenditure compared to East Asia. On the Asian side, Taipei and Daejeon are somewhat exceptional because of their large and medium cluster size but low levels of networking. Overall, the outcomes suggest that multi-scalarity has many ‘faces’, ranging from relatively modest global networks alongside large clusters to relatively strong global networks alongside small clusters. For example, in–depth study of Lausanne (until 2000 among the 15 best performing clusters, followed by a relative decline) has learned that a relatively small cluster could develop worldwide networks due to one or few worldwide famous researchers. However, in next years it was difficult, just due to these networks, to build more capacity within the cluster and increasing the benefits from networking came to a halt.

>>Insert Figure 3

6. DISCUSSION

The photovoltaic sector has undergone an accelerated growth since around 1998, which did not result in a longer period of growth, and since around 2003, which did result in prolonged growth. This prolonged growth has manifested itself in the same relatively strong clusters: Tokyo, Osaka, San Jose, Seoul, Taipei and as the only European cluster in the top, Frankfurt. Compared with earlier periods, Lon Angeles, New York and Boston have lost some of their position. In a second step of the study, a model of inventive performance of clusters was tested, for which the data have been derived from bibliographic sources and databases. Three sets of influences were tested, agglomeration factors, network factors and regional research/innovation quality, for the years 2009-2011, in-so-far this was possible with bibliographic data. The results indicated an almost equally strong and positive influence from agglomeration factors and network factors, while the influence of regional quality turned out to be somewhat weaker. In addition, interaction between cluster size and size of the network tends to have a positive influence on inventive performance, indicating that various combinations of large and small clusters with large and small networks, work out positively, and that multi-scalarity can also be diverse. This could be illustrated with the five strongest clusters, mostly in Asia, by their high scores on both factors, except for one cluster. Next strongest clusters in inventive performance, all in the US and one in Europe, were facing the combination of a medium-sized cluster with large network size. Cultural factors (language) and longer traditions of collaboration abroad could explain the differences, but the relatively strong networking was not sufficient to enable to remain on the top of best performing clusters.

This study shows that testing an invention model of clusters is feasible using bibliometric data, which is promising for research in other sectors, as bibliometric sources produce one of the few consistent data bases. However, the study also shows some of the limitations. First among them is the propensity for measurement errors and uncertainty due to the process of geocoding and cluster identification. To avoid undue influence of these errors, smaller clusters are excluded from the study. Second, although a simple and transparent method for cluster identification, the use of bibliometrics means that only one dimension of the sector, and one dimension of innovation, is being measured. It is therefore likely that the method ‘overlooks’ clusters which may have significance in terms of production or production-related R&D but not in terms of more general or basic R&D that is eventually published as patents or peer-reviewed scientific publications. Since only photovoltaics was explored, different sectors may display significantly different agglomeration and network effects. Third, many of the indicators used in the model, and the way in which they are applied, are novel and may therefore be further improved and validated.

Furthermore, the research findings presented hold only for the photovoltaics sector, a high-technology sector that has undergone rapid growth during the past decade, something which could well influence the factors of inventive performance themselves. That is to say: the findings presented here may not apply to other sectors. So repeating this approach to other sectors seems very worthwhile. The automated geocoding of patent and scientific publications, applied in this study, makes it possible to identify inventions and research in other sectors taking place in the same cluster, as ‘all that’s required is computing time’. And finally, we suggest to further increase understanding of multi-scalarity in networks in case-based in-depth research using interviews, for example, to compare changes in within cluster networks and in external networks between clusters that lost position since 2000, such as Stuttgart, and clusters that enhanced position, such as Taipei.

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Figure 1 Research model

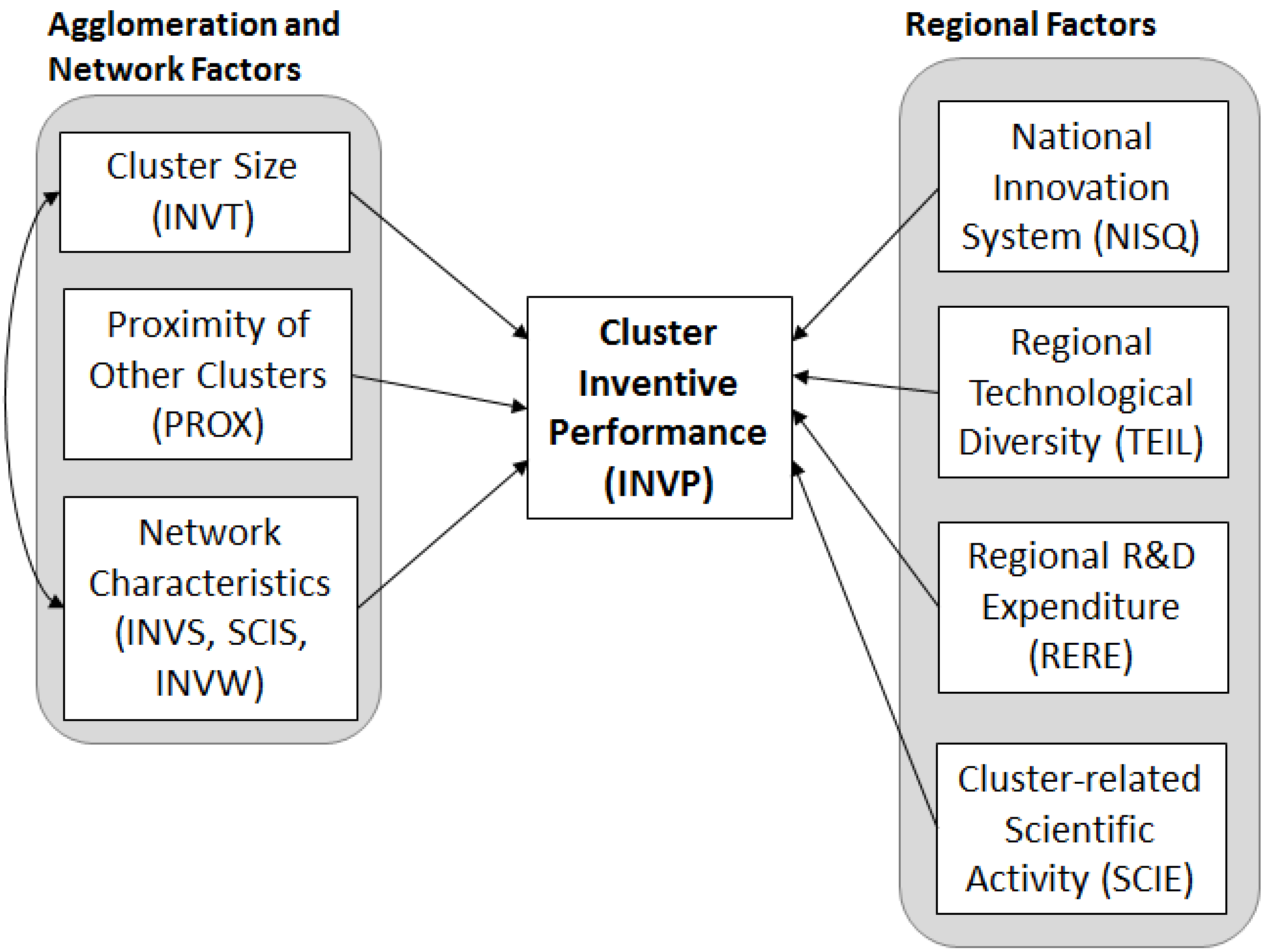
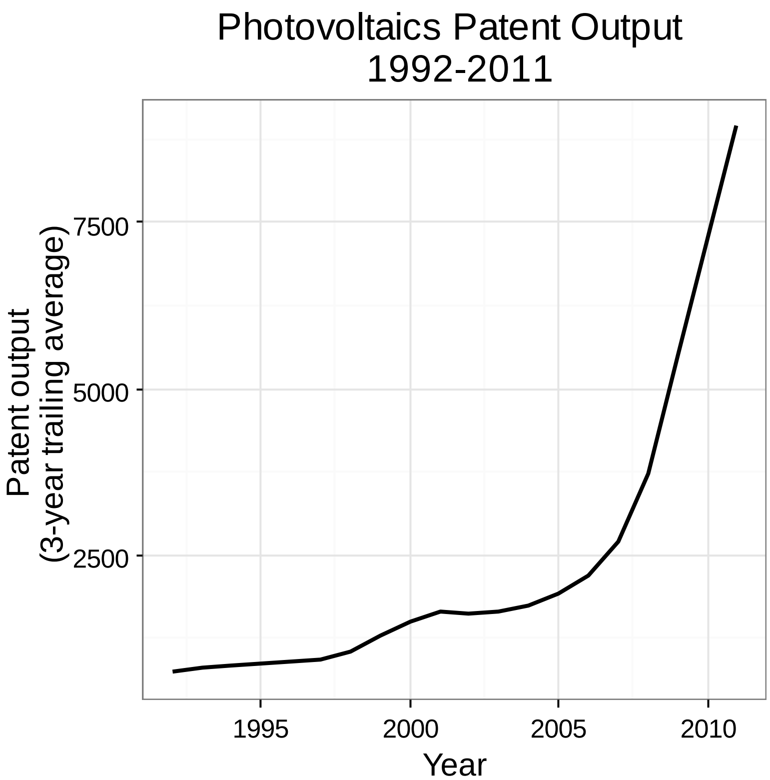


Figure 2 Inventive performance of global PV sector



Source: PATSTAT Spring 2015.

Figure 3   Network size (INVS) and cluster size (INVT) of 40-largest photovoltaics clusters during the 2011 period