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Innovation Capability, Network Embeddedness and Economic Performance: Profiling Solar Power Innovators in China

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ABSTRACT

This paper discusses the technological upgrading of China in photovoltaics technology. It explores the patterns of innovation and network-embeddedness and their impact on economic performance at the firm level. Identifying the main innovators over 1995-2014 with patent and market-share indicators, the landscape of their activities is inspected through two hierarchical cluster analyses in parallel: First, against the quantity, quality and diversity of patents, and second, against global-integration, component-size and position in technological knowledge networks. The resulting clusters are cross-related to understand their interrelations with age, size, turnover and productivity of actors. The multivariate analysis of variance shows a significant relationship between innovation-network concurrency and the age, turnover and productivity. Global-integration in small-world networks is significantly related with economic performance. Quality of innovation shows higher importance than quantity and diversity. While specialization in high-tech fields has positive impact on turnover, production-oriented firms with low-tech focus have higher productivity.

KEYWORDS

innovation system; solar photovoltaics; China; patent profiles; network embeddedness patterns; cluster analysis; MANOVA; concurrency matrix; economic performance; productivity; technological upgrading; emerging economy

JEL CLASSIFICATION

D24; D85; O31; O34; Q42; Q55

BIOGRAPHICAL STATEMENT

Mahmood Shubbak is a researcher in the Faculty of Business Studies & Economics at the University of Bremen. His research interests are related to innovation systems and technology upgrading of emerging economies. He obtained his PhD in Economics from the University of Bremen in 2018. He holds a Bachelor and Master degrees in Mechatronics, ICT and Automation Engineering.

1. INTRODUCTION

Technological upgrading of emerging economies comprises multi-level structural change industrially, organisationally and technologically (Jindra, et al., 2015; Radosevic & Yoruk, 2016). Throughout these processes, innovation can both lead to, and result from successful catching-up (Lee, 2013). Innovation has long been considered as a main driver of economic development at the macro-level (Schumpeter, 1934). Theoretically, it has been shown that within an industry, there is a significant correlation between innovative activities undertaken in companies and the financial performance measured by growth in assets, turnover, and productivity (Pavitt, 1963, p. 207). However, empirical findings about the relationship between innovation capability and firm performance on the micro-level have been mixed. While many studies validated a positive impact (Geroski & Machin, 1992; Crepon, et al., 1998; Cainelli, et al., 2006; Andries & Faems, 2013), others found no or even negative relationships (MacDonald, 2004; Artz, et al., 2010).

This suggests a puzzle, which we attempt to answer by inspecting the role of network embeddedness in shaping and facilitating the relationship between innovation and economic performance. An increasing consensus in the academic literature has recently emerged on the significant effect of embeddedness in interfirm networks on the innovative and economic performance of firms (Powell, et al., 1996; Gilsing, et al., 2008). In this paper, we will suggest that the impact of innovation capability on economic performance at the firm level is highly heterogeneous across different network-embeddedness patterns.

Accordingly, the paper aims to disentangle the combined effects of innovation-capability and network-embeddedness patterns on age, size, and financial performance of organisations. Considering the technological upgrading within the solar photovoltaics (PV) industry in China, we address the following research questions:

- Which are the main actors in the Chinese PV innovation system? Which characteristics do they have?
- Which patterns of innovative activities and knowledge network embeddedness could be found in the system?
- What is the relationship between these patterns and economic performance?

To answer these questions, the paper is organized in six sections. The next section reviews the relevant literature. Section 3 introduces the research methodology, data sources and indicators used in the empirical analysis. In section 4, the results concerning main actors, innovation patterns, network patterns and concurrency analysis are presented. Section 5 synthesises the main empirical findings and tests the research hypotheses. Finally, section 6 draws some conclusions and highlights the research limitations.

Information Box: Broader Context and Conceptual Framework

To meet the challenges posed by climate change, renewable energy sources are widely considered as a clean and sustainable alternative to the conventional sources (fossil fuels). However, the differences in economic feasibility between both types (in terms of initial capital and megawatt-hour costs) have long constituted a key obstacle for renewable sources to become a major means of generating electricity at the global level. On the other hand, three parallel paths could interactively lead to the grid parity: – first, product and process innovations, second, mass production and vertical integration, and third, government subsidies for both supply and demand sides of renewable sources. While the latter two paths concern with reducing the manufacturing and operational costs, innovation is more related to increasing power conversion efficiency. To understand the interrelated roles of the three parallel paths, the use of the conceptual framework of innovation systems sounds reasonable.

Technological Systems of Innovation:
Innovation is not exclusively restricted inside firms, it is rather an outcome of active interrelations between various firm and non-firm entities within complex systems (Günther, 2015). The systemic approach of studying innovation was developed in the late 1980s at a national level (Freeman, 1988; Lundvall, 1992) and later, at sectoral and technological levels (Carlsson & Stankiewicz, 1991; Breschi & Malerba, 1997). The significance of this framework lies in its comprehensiveness and inclusion of all the important factors influencing innovation (Edquist, 1997). Carlsson & Stankiewicz (1991, p. 111) defined technological innovation systems (TIS) as "network of agents interacting in a specific economic area under a particular institutional infrastructure... and involved in the generation, diffusion, and utilization of technology". From that perspective, TIS aims at understanding innovation by considering three analytical blocks – (1) the innovative actors, (2) the network structure of their interactions, (3) the institutional framework.

Nonetheless, given the instability and politics-dependent nature of government subsidizing programs[1], innovation and mass production are considered more important for renewables to become competitive per se in the global energy market. Accordingly, the focus of this paper is on the characteristics of innovators (actors), their technological knowledge networks (interactions), and associated economic performance (productivity). The institutional framework of the TIS is out of the scope of this paper.

2. THEORY AND HYPOTHESES

2.1 The Influence of Innovation Capability on Economic Performance

The impact of innovative activities on economic performance has long been at the centre of the attention of many studies (Franko, 1989; Geroski & Machin, 1992; Schmidt, 1995; Lester, 1998; Evangelista & Vezzani, 2010; Hashi & Stojčić, 2013; Adeyeye, et al., 2013). Cainelli, et al. (2006) found a significant positive impact of innovation on economic growth and productivity of firms. Andries & Faems (2013) highlighted the positive contribution of innovation performance and patenting activities to the profit margins of both SMEs and large firms. Furthermore, Silva et al. (2017) shown a positive impact of technological innovation on firms' economic and strategic export performance. In this sense, we expect a positive impact of innovation capability of firms on their economic performance.

> ***Hypothesis 1a:*** *The innovation capability of an organization is positively related to its economic performance.*

Malerba & Orsenigo (1997) studied the sectoral patterns of innovative activities, showing that although turbulent innovative activities are fundamental for industrial evolution (creative destruction), persistent innovative activities by large established firms are also important for deepening technological capabilities (creative accumulation). They found that effective patterns of innovation depend mainly on the structural characteristics of the technology and its related learning processes. As innovative companies get bigger, they usually accumulate more technological knowledge, financial assets, and market experience becoming better able to invest in substantial research and development projects as well as to introduce more innovations. Therefore, we expect a positive relationship between companies' age and size on the one hand, and their innovation capability on the other. Stated more formally:

Hypothesis 1b: *The age of an organization is positively related to its innovation capability.*

Hypothesis 1c: *The size of an organization is positively related to its innovation capability.*

However, the sole consideration of the quantity of innovative activity throughput can be misleading. Further characteristics of innovation can be of a higher importance, such as its quality and diversity. Innovations of high quality can have a significant impact on the value and adoption rates of final products, and thus on the market share and revenue of their developers.

Sampson (2007) studied the impact of technological diversity and alliance organizational form on firm innovative performance highlighting the importance of alliances along with moderate technological diversity for innovation. Furthermore, Leten, et al. (2007) found an inverted U-shaped relationship between the technological diversification of a firm and its performance, where technological coherence plays a moderating role. While Hitt, et al. (1997) emphasized the importance of product diversification in moderating the negative effect of international diversification on firm performance at the first stage of internationalization, Lu & Beamish (2004) showed positive net gains up to a certain point at the second phase of multinationalism. This leads to the following hypothesis:

Hypothesis 1d: *The quality of innovation is more effective than its quantity and diversity in improving economic performance of organizations.*

2.2 The Influence of Network Embeddedness on Economic Performance

An increasing unanimity in the literature has recently emerged on the significant effect of network-embeddedness on innovation and economic performance of organizations (Hagedoorn, 1993; Rowley, et al., 2000; Gilsing, et al., 2008). Ahuja (2000) showed that both direct and indirect ties between firms in collaboration networks within chemicals industry have positive impact on innovation. A similar significant relationship between embeddedness and innovation could be found in semiconductors industry (Stuart, 1998), steel industry (Rowley, et al., 2000), biotechnology (Powell, et al., 1996), and food manufacturing (Tsai, 2001).

Koka & Prescott (2008, p. 658) argued that types of network positions are likely to impact firm performance differently under different contexts. Tsai (2001) found that occupying central network positions can provide organizational units with access to new knowledge developed elsewhere, which can yield more innovations and better economic performance, provided that these units have the necessary absorptive capacity. Gilsing, et al. (2008, p. 1729) argued that "*position alone does not tell the full story*", a successful outcome also depends on technological distance and network density. The results of (Uzzi, 1996) suggested that, up to a threshold point, network embeddedness could enhance economic effectiveness and competitiveness. Rowley (2000, p. 384) found that the strength of network ties influenced returns on assets contingent upon industry factors. Powell, et al. (1996) found positive impact of network diversity on firms' rate of growth. Goerzen & Beamish (2005) stressed that firm strategies of either being focused in homogeneous networks, or having very diverse alliances, resulted in superior performance compared to the majority firms with moderate network diversity. Furthermore, as organizations get bigger, additional ties to their established networks are expected to be added, enhancing its embeddedness and network position (Wang, et al., 2018). In sum, this leads to the following hypotheses:

Hypothesis 2a: *The network embeddedness of an organization is positively related to its economic performance.*

Hypothesis 2b: *Older organizations are more embedded in networks.*

Hypothesis 2c: *Larger organizations are more embedded in networks.*

2.3 The Combined Influence

Although the effect of innovation and network embeddedness on economic performance is well established in academic literature, it is nonetheless only discussed on an individual basis. This leaves an important part of the image unclear. In other words, the combined effect of both dimensions is still to be addressed[2]. Considering the research gap introduced in section 1, we examine the following thesis: the different effects of innovation capability on economic outcome are attributed to different network structures or embeddedness levels. So that, we expect a positive effect of the interaction between innovation capability and network embeddedness on economic performance. Stated more formally:

Hypothesis 3: *The innovation capability of an organization is more positively related to economic performance when the organization has a high network embeddedness level.*

To test the hypotheses of this paper, a micro-level analysis is conducted within a specific technological field in a specific country, namely solar photovoltaics (PV) in China.

The contributions of this paper are threefold: First, it provides a detailed profiling of the main actors within the innovation system of PV technologies in China. Second, it uniquely defines two sets of patterns for both innovation-capability and network-embeddedness. Third, it introduces the novel analytical tool of 'concurrency matrix' to study the interaction between innovation and network patterns and its resulting impact on economic performance of firms.

3. DATA AND METHODS

Among the wide range of existing renewables, PV is considered as "*the cleanest and safest technology with which to generate electricity even at the GW production scale*" (Hegedus & Luque, 2010, p. 24). China has recently become the main global player in both production and deployment of PV crystalline-silicon (c-Si) modules (UNEP, et al., 2010; Marigo, 2007). In 2008, it became the dominant force in PV production, controlling one-third of the global market (Fu, 2015). Later, since 2011, its market share has stabilized at the level of 60% (Jäger-Waldau, 2013). Furthermore, the country has experienced an exponential growth rate in terms of cumulative installed PV power since 2011, becoming the world's leader since 2015 with more than 43 GW, and reaching the level of 78 GW in 2016 (British Petroleum, 2017).

Against this rapid growth of China's share in both supply and demand sides of PV, and being inspired by the importance of innovation, networking, and mass production processes in enhancing the stature of PV technologies in the global energy landscape, this paper studies the characteristics of the leading actors within the technological innovation system of PV in China using a combination of patent-, network-, and cluster analysis.

For the empirical analysis, patent data from PATSTAT (the Worldwide Patent Statistical Database) are mainly used. Pavitt (1985, p. 82) argued that patent statistics can be used as a proxy of innovative and not only inventive activities, considering the fact that they are usually filed "*over the whole cycle of development and commercialisation of an innovation*". Zahra & George (2002) considered patent filings to evaluate the exploitation element of absorptive capacity at firm level. Despite the well-known limitation for using patents as a proxy for innovation (Archibugi, 1992; Kleinknecht, et al., 2002), patent statistics are, nonetheless, widely considered as the "*best available output indicator*" for innovation capability (Sawang, et al., 2017, p. 157; Freeman, 2004).

To extract PV relevant patent applications, we use the identification scheme developed by Shubbak (2017a). It offers a comprehensive definition of different technologies along the PV value chain. Using a classification scheme mainly based on IPC classes, Shubbak (2017a) defines six PV groups – solar cells, panels, electronics, monitoring, energy storage, and solar-powered portable devices. The scheme provides further detailed subgroups of the embodied technologies (see the technological subgroups in figure 4).

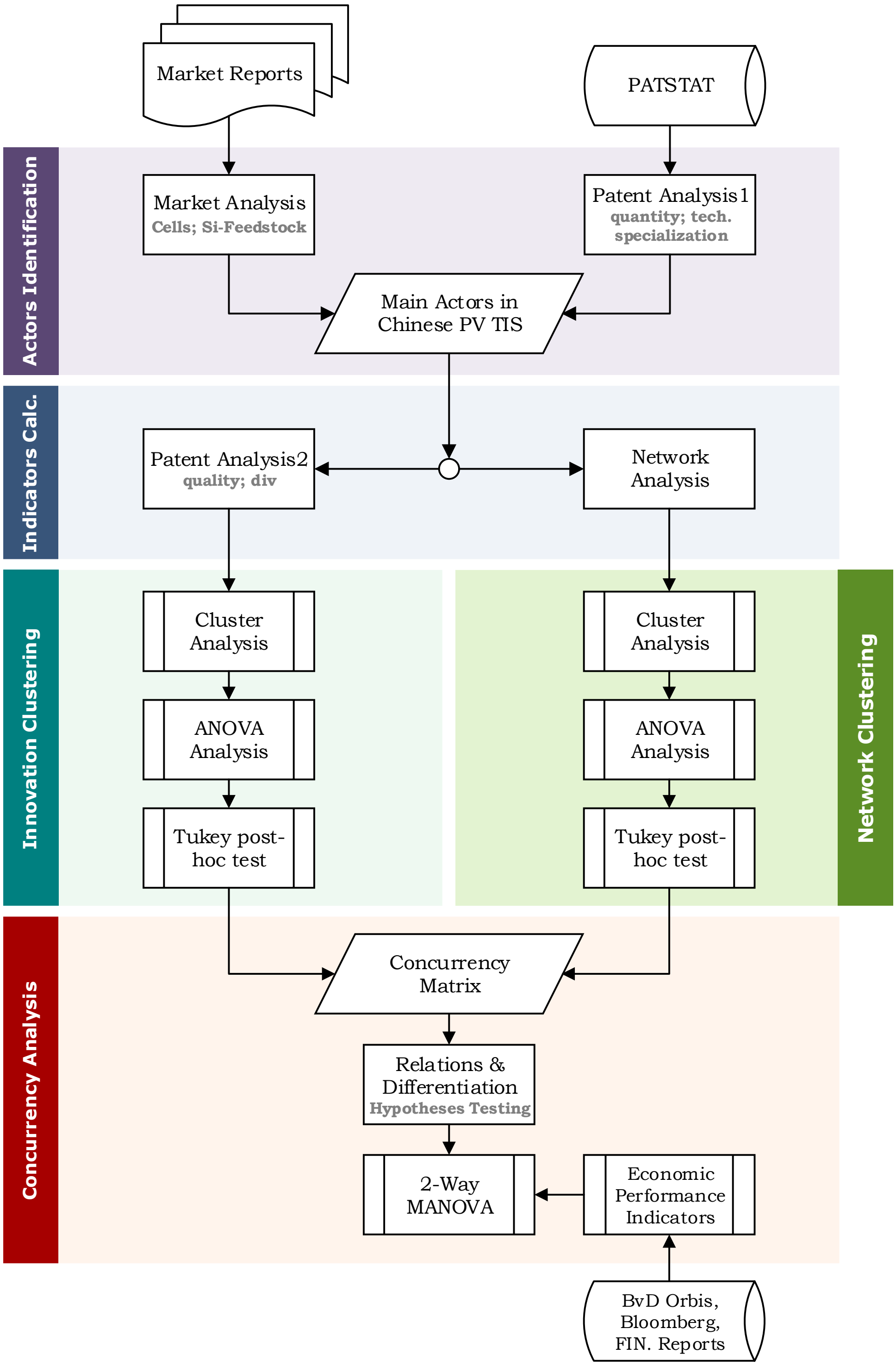
The quantitative analysis of this paper is carried out based upon four stages (figure 1):

1. Identification of main actors

In this stage, the main actors in the Chinese PV system of innovation are identified using patent and production data. The resulting list of innovators and active actors is thus compiled from the following sources:

- The largest purified-silicon feedstock producers in China with more than 1% share in the global market. *[Data source:* (Yu, et al., 2016; Roselund, 2016; Shubbak, 2017b)*]*.
- The largest Chinese manufacturers of c-Si cells with more than 1% share in the global market. *[Renewable Energy World* (Mints, 2014)*; dataset of* (Brown, et al., 2015)*, and* (Shubbak, 2017b)*]*.
- The top 5% transnational patent applicants, within the entire PV system, for inventions taken place in China. *[PATSTAT 2015b based on* (Shubbak, 2017a)*]*.
- The top ten patent assignees for inventions within the main technological groups of the system (cell technologies, panels, and electronics). *[PATSTAT 2015b based on* (Shubbak, 2017a)*]*.

Figure1: Research Methodology Flowchart



Author's own elaboration

2. Calculation of indicators

In this stage, quantitative measures of innovative performance and collaboration network embeddedness are calculated for each actor in the innovators list. This is done, first, through patent analysis of the quantity, quality, and diversification of inventive activities, and second, through social network analysis of actor positions and global integration in patent co-applicant networks. A full list of indicators and data sources used throughout this paper is contained in table 1.

Table 1: Variable Definitions and Data Sources

Variable	Description	Data Source
Innovation Performance (Inventive Activities)		
Pat	Quantity: number of transnational patent applications filed by an actor during 1995-2014	PATSTAT 2015b, PV patents identified and classified using (Shubbak, 2017a)
Fwd_Citn	Quality1: Average of forward citations to the patents of an actor over patent age. Proxy for techno-economic impact	
High_tech	Quality2: Percentage of high-tech patents of the total patent applications filed by an actor	
Div	Technological Diversification of patent applications of an actor	
Network Embeddedness		
Deg	Weighted degree of actor node in the PV co-patenting network in China over 1995-2014. Proxy for inventive collaboration	PATSTAT 2015b, (Dominguez Lacasa & Shubbak, 2018)
Btwn_cn	Betweenness centrality of actor node in the PV co-patenting network in China over 1995-2014. Proxy of actor's importance for knowledge transfer over technological network	
Clust_coef	Clustering coefficient of actor node in the PV co-patenting network in China over 1995-2014. Proxy for embeddedness in small-world network	
Com_Size	Network component size: number of nodes in the component (community) to which an actor belongs	
Frgn_coll	Collaboration with foreigner actors: percentage of non-Chinese actors in network component to which an actor belongs	
Characteristics and Economic Performance		
Age	Age of an actor: number of years since the establishment of an actor till 2015	BvD Orbis database, Bloomberg LP data; Forbes lists; Firm websites and financial reports
Turnover	Economic performance: operating revenue (turnover) of an actor in 2015 (values in million US dollars)	
Employees	Size: number of employees of an actor in 2015 (in thousands)	
Productivity	Operating revenue over the number of employees. Proxy for the efficiency of economic activities done by an actor	

With regard to the innovation dimension, the following variables were calculated:

The number of transnational patent applications (*Pat*) is used as a proxy for the quantity of innovation. It is calculated based on (Frietsch & Schmoch, 2010) as the number of patent applications filed at the European Patent Office (EPO), and international patent applications filed under the Patent Cooperation Treaty (PCT), avoiding double counting of EPO applications at the international phase (equation 1).

$$Pat = |TN|\ ; TN = \{x \mid x \in EPO \cup PCT\} \qquad \text{(Equation 1)}$$

The two types, EPO and PCT, are the only cross-border enforceable patents, and are thus expected to have high economic and technological value.

Forward citation index (*Fwd_Citn*) is used as a proxy for exogenous quality of innovation (technological impact of inventive activities). It is calculated for each actor as the average number of citations received *(C_i)* over patent life time[3] *(age)* for all transnational patent applications *(N)* filed by the actor (equation 2).

$$Fwd_{Citn} = \frac{1}{N}\sum_{i=1}^{N}\frac{C_i}{age_i} \qquad \text{(Equation 2)}$$

The share of high-tech patents in the actor's portfolio (*High-tech*) is used as a proxy for endogenous quality of innovation. The indicator is based on (Shubbak, 2017a).

The technological diversification index (*Div*) reflects the extent to which an actor is engaged in inventive activities within several technological groups across the PV value chain (Leten, et al., 2007; Suominen, et al., 2017). It considers the diversity of patent portfolio of an actor calculated as the complement of normalized Herfindahl-Hirschman index (Hirschman, 1964) for patent shares *(s_i)* of PV main groups *(N)*. (equation 3)

$$Div = \frac{1}{N-1}\left(1 - N\sum_{i=1}^{N} s_i^2\right) \qquad \text{(Equation 3)}$$

<u>As for the network embeddedness dimension, the following indicators are considered[4]:</u>

The weighted degree (*Deg*) of an actor in network analysis represents the total number of ties that directly link the actor with its patent co-applicants. If two actors have more than one joint patent, the additional collaborations are added to their degrees. Consequently, this indicator reflects the total number of collaborations for each actor.

The betweenness centrality (*Btwn_cn*) of an actor reflects the importance of its position in connecting several components of the network, and thus in transferring knowledge. The indicator is measured as the fraction of shortest paths between other nodes in the network that pass through the designated node (Freeman, 1977). (equation 4)

$$Btwn\_cn = \sum_{s\neq n_i\neq t}\frac{\sigma_{st}(n_i)}{\sigma_{st}} \qquad \text{(Equation 4)}$$

Where: s, t: represents any other nodes in the network; σ_{st}: is the total number of shortest paths between s and t; $\sigma_{st}(n_i)$: is the number of shortest paths between s and t that pass through the designated node n_i.

The size of network component (*Com_size*) is calculated as the number of nodes in the connected subgraph to which an actor belongs. It reflects the overall number of co-patenting partners that are reachable by the actor either directly or indirectly.

The clustering coefficient (Clust_coef) of a node reflects the tendency of its neighbourhood to link together. It is measured as the ratio of existing links *(e_i)* between a node's neighbours *(k_i)* to the maximum possible links they could have (equation 5). High clustering coefficient is considered as an indicator for small-world networks.

$$Clust\_coef = \frac{2e_i}{k_i(k_i-1)} \qquad \text{(Equation 5)}$$

Finally, the global integration indicator (Frgn_coll) reflects the ratio of collaborations between the designated actor and foreigner (non-Chinese) actors. It is calculated as the ratio of foreigners in the network component of the concerned actor.

For industrial actors which have no patent applications and thus not appearing in co-patenting network, the diversity, centrality and clustering coefficients are set to -1.

3. Cluster Analysis

In this stage, the calculated indicators are used to assign actors into specific groups through two cluster analysis processes in parallel. The use of cluster analysis as a tool of discovery spans several disciplines in both natural and social sciences. Besides its use for pattern recognition, classification, and taxonomy construction, cluster analysis is widely used to reduce large complex datasets into meaningful homogeneous groups. The resulting groups can further serve as a basis for classifying new observations or developing inductive generalizations (Anderberg, 1973). Consequently, the purpose of cluster analyses in this paper is to explore the patterns of innovative activities (INNO) as well as the patterns of network embeddedness (NET) within the technological system of PV, and to classify its main actors accordingly.

To do so, the four innovation-performance indicators are used in the first cluster analysis, while the five network-embeddedness variables are used in the second. Both cluster analysis are of hierarchical type, utilizing Ward's method, considering Euclidean distance as similarity measure, and normalizing variables to the 0-1 interval (Anderberg, 1973; Mooi & Sarstedt, 2010).

The two cluster analyses are followed by robustness check of variance ratio criterion through one-way ANOVA. The purpose of this step is to insure significant differences among group mean values. Furthermore, a Tukey HSD (honest significant difference) post-hoc test is performed for better understanding of the resulting clusters and thus labelling them. All the statistical and cluster analysis operations throughout this paper are conducted using IBM SPSS Statistics, version 24.0. (IBM Corp., 2016).

4. Co-evolution analysis (concurrency matrix and economic performance)

In this stage both cluster sets are integrated into one concurrency matrix to study their interaction and confluence on economic performance of actors. Multivariate analysis of variance (MANOVA) is performed for this purpose, having actors' age, turnover, number of employees, and productivity as dependent variables.

The statistical general linear model of MANOVA is shown in equation 6. Where Y_{ij} represents the vector of observations for INNO treatments in NET blocks, ν is the overall mean vector, α_i is the effect of INNO on the dependent variables, β_j is the effect of NET on the dependent variables, γ_{ij} is the non-additive effect of INNO*NET interaction on the dependent variables, and ε_{ij} is the experimental error vector.

$$Y_{ij} = \nu + \alpha_i + \beta_j + \gamma_{ij} + \varepsilon_{ij} \qquad \text{(Equation 6)}$$

To insure a temporal order between the independent and dependent variables, the data for clustering variables spans from 1995 to 2014, while the general characteristic and economic performance indicators are considered for 2015. Nevertheless, it is worth stressing that causality is yet "*a logical and theoretical task that extends beyond the bounds of statistical analysis*" (Grice & Iwasaki, 2007, p. 201).

Finally, the complete image compiling the three analytical dimensions is illustrated in circular genome visualization using (Krzywinski, et al., 2009).

4. RESULTS

4.1 The Main Actors within the Chinese PV System

Throughout the patent and market analysis conducted in this section, 37 organisations were identified as the main actors in the innovation system (table A1 in the appendix). Despite the relatively small size of this sample, the identified actors have however a prominent place within the system. They were accountable for 31% of global Si-feedstock production and 34% of global c-Si cell manufacturing during 2010-2015. They held significant shares of the Chinese PV production in the same period, 60% of c-Si cells and 90% of feedstock. Furthermore, they were involved in co-patenting network components accountable for 41% of the overall Chinese transnational patent applications over 1995-2014. The detailed results are explained in the following subsections.

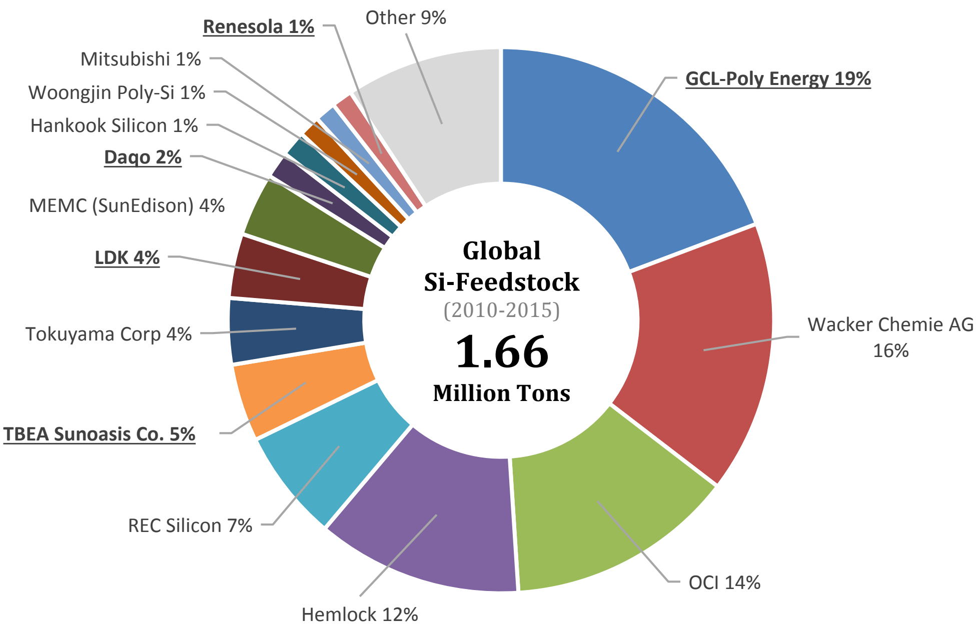
4.1.1 Production and Market Share

To identify the most active actors in the technological system of PV in China, the global markets of solar cells and purified silicon feedstock are first considered. c-Si is the dominant technology in the global market of solar PV. In 2015, it had 93% share of the total produced capacity of PV cells. It also formed the main focus of Chinese production. However, among the manufacturing process of c-Si cells, the purification of polysilicon into solar-grade of 99.999% and its subsequent processes of ingot production are considered the core technology (Si-feedstock) (Mertens, 2014, pp. 99-102).

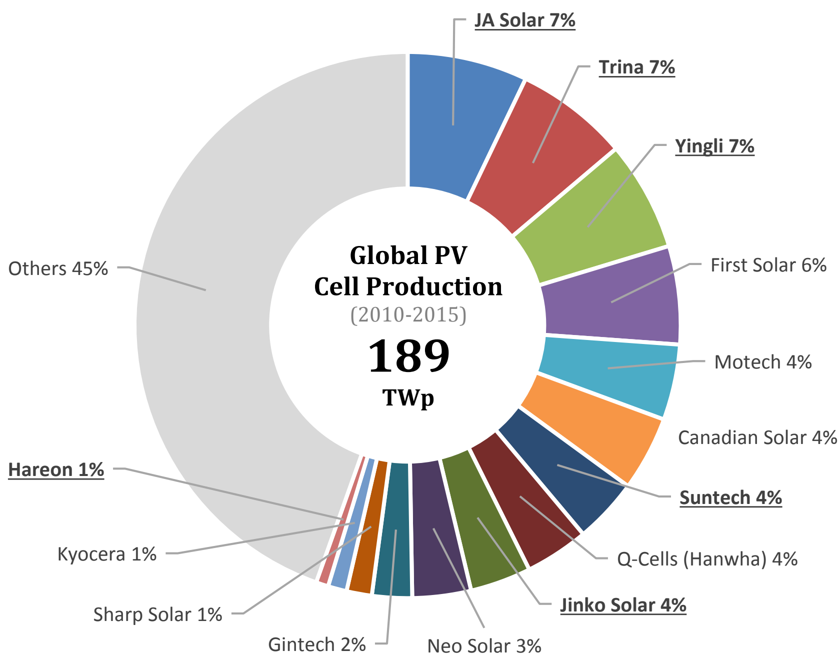
Figure 2 shows the market shares of global PV producers during 2010-2015. As illustrated in figure 2a, the Si-feedstock global market is dominated by 14 firms sharing 91% of the 1.66 million metric ton market. Among those, 5 Chinese producers accountable for 31% share of the global market can be identified (underlined and shown in bold in figure 2a). On the other hand, the c-Si silicon cell market is more fragmented with the top 14 firms holding 55% share of the 189 TWp market (figure 2b). 6 Chinese manufacturers of solar cells with total market share of more than 30% are identified (underlined and in bold).

Figure 2: Market Share of Global PV Producers 2010-2015

a. Global Si-Feedstock Production



b. Global PV Cell Production

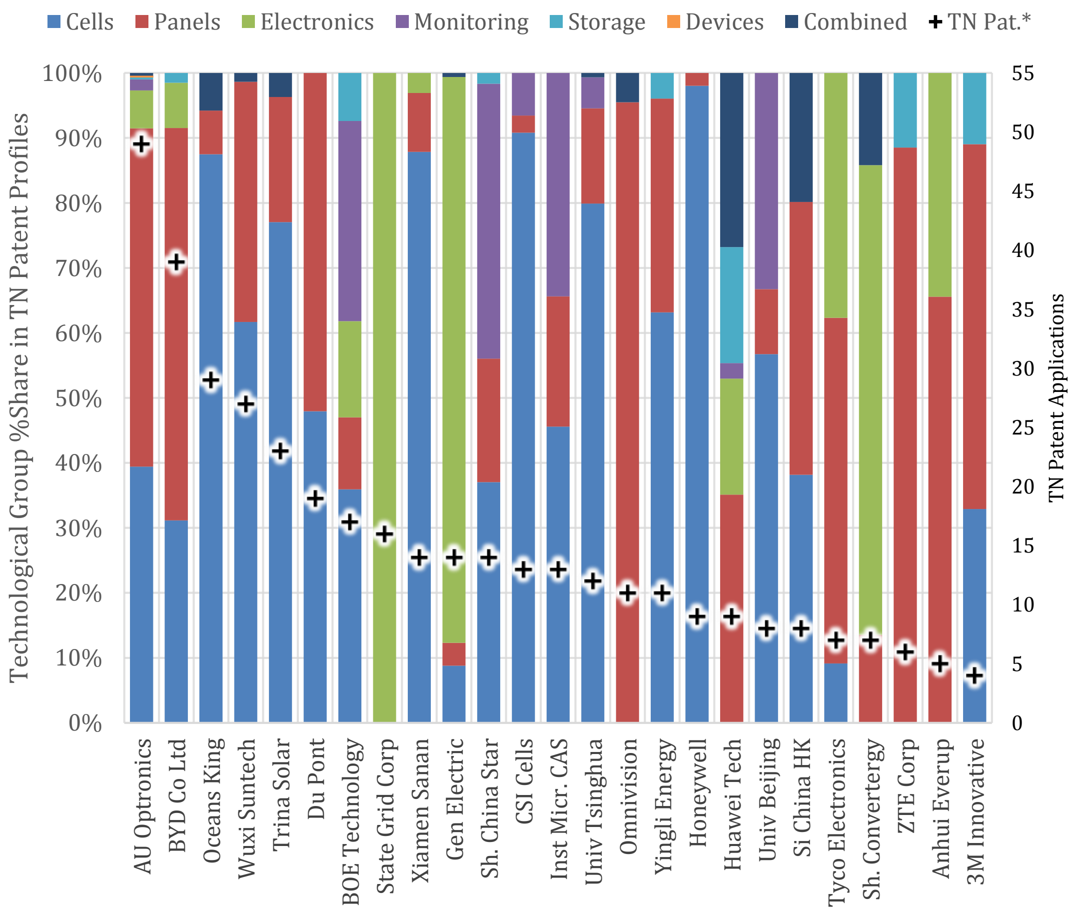


Author's own elaboration. Data compiled from the following sources: (Yu, et al., 2016; Roselund, 2016; Mints, 2014; Brown, et al., 2015; Shubbak, 2017b)

4.1.2 Inventive Activities (Technological Profiles)

To have a deeper insight into the actors driving the development of technological capabilities in the TIS of China, the patent analysis focuses next on the specialization profiles of the top 5% transnational patent applicants during 1995-2014 (figure 3). The resulting 25 organisations directly accumulate 32% of the total Chinese transnational patents in PV technologies. Interestingly, 3 Chinese universities and 8 foreigner companies are found among these organisations. Figure 3 shows the patenting stocks of those top 25 applicants along with their technological profiles in the main PV groups. Similar to the overall trend within the Chinese transnational patent landscape in PV, the leading organisations are mostly specialized in cells and panels with only three exceptions. These are the State Grid Corp China, the American multinational enterprise General Electric, and the Chinese company Shanghai Convertergy, where high specialization in electronics is noticed.

Figure 3: PV Technological Specialization of the Top 5% TN Patent Applicants in China

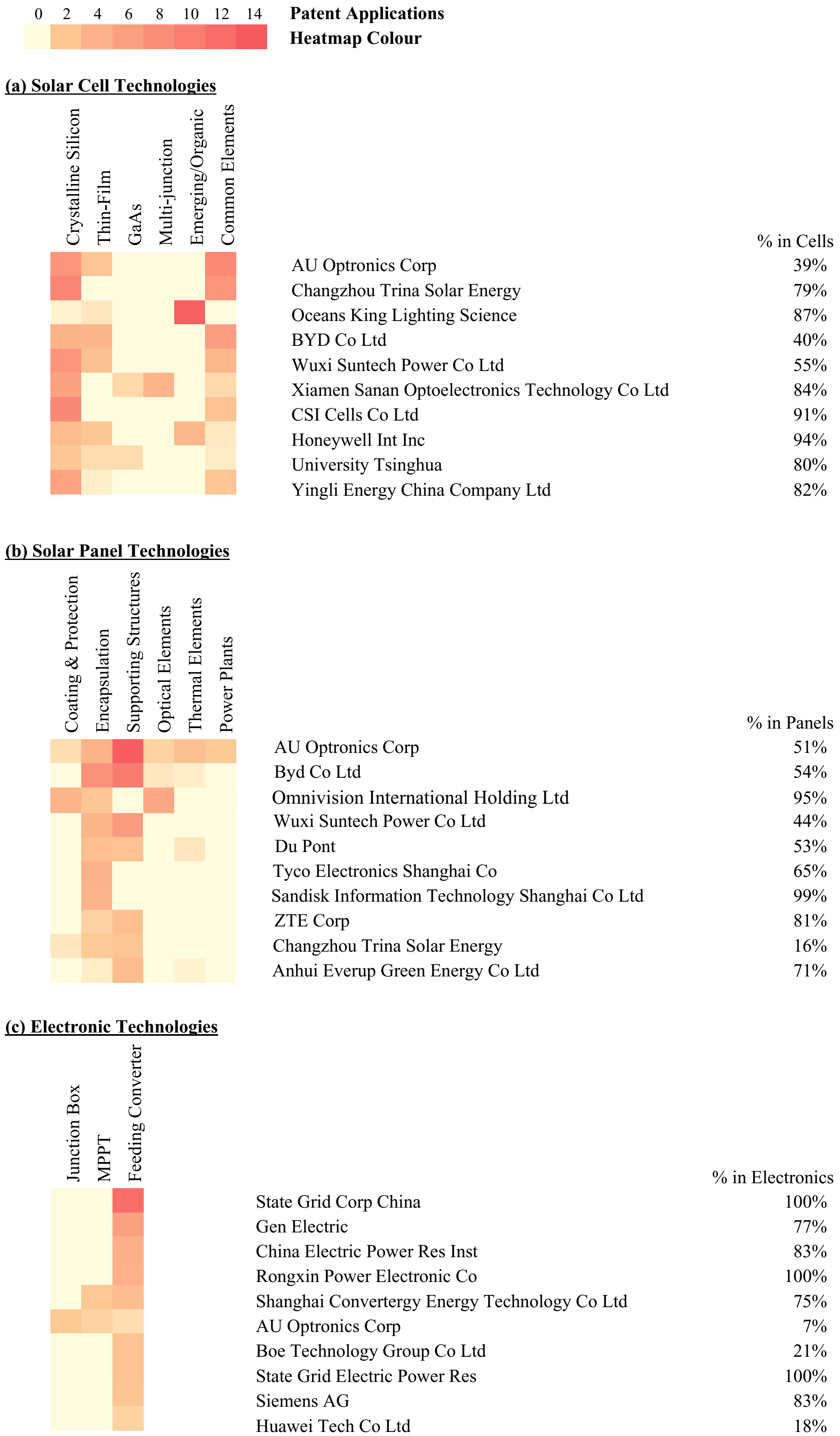


Actors in this figure are accountable for 32% of the total Chinese transnational patents in PV sector.
* figures are shown in secondary axis. Data source: PATSTAT 2015b. Authors' own elaboration.

Going deeper to the next level of analysis, the technological profiles of the leading actors within the main three PV groups are considered. Within each field of solar cells, panels, and electronics, the top 10 patent assignees are listed against their patent shares in technological subgroups (figure 4). As shown in figure 4a, the specialization of solar cell innovators is highly focused in c-Si cells and elements. On the other hand, encapsulation and supporting structures form the specialization fields for solar panel innovators, while feeding converter circuits are on focus of electronics innovators. All applicants that appear in the top-10 innovator lists (figure 4) are considered for the research sample.

Figure 4: Technological profiles of the top 10 PV patent assignees in China during 1995-2014.

Heatmap representation of transnational patent applications in PV Cells, Panels and Electronics



Data Source: PATSTAT 2015b. Author's own elaboration

4.2 Cluster Analysis

Table 2 contains the descriptive statistics and the correlations between variables for all observations in the sample.

Table 2: Descriptive Statistics and Correlation Matrix

	Variable *	Mean	Std. Dev.	Min	Max	1	2	3	4
1	Pat	11.27	10.80	0	49	1.000			
2	Fwd_Citn	0.45	0.40	0	1.83	0.378	1.000		
3	High_tech	0.35	0.35	0	1	0.019	0.173	1.000	
4	Div	0.29	0.47	-1	0.86	0.405	0.412	0.064	1.000
5	Deg	21.65	24.06	-1	92	0.792	0.398	0.225	0.221
6	Btwn_cn	462.62	1210.72	-1	6717	0.248	0.181	0.137	0.072
7	Clust_coef	0.27	0.51	-1	1	0.022	0.104	0.273	0.579
8	Com_size	33.49	39.59	0	134	0.280	0.180	0.292	0.207
9	Frgn_coll	0.11	0.19	0	1	-0.013	0.258	-0.088	0.052
10	Turnover **	13.50	25.80	0.003	117	0.009	0.349	0.457	0.099
11	Employees	70,629	166,380	50	927,839	0.130	0.329	0.473	-0.019
12	Age	41.05	44.71	3	168	-0.100	0.313	0.230	0.128

		5	6	7	8	9	10	11	12
5	Deg	1.000							
6	Btwn_cn	0.500	1.000						
7	Clust_coef	0.041	-0.064	1.000					
8	Com_size	0.522	0.628	0.240	1.000				
9	Frgn_coll	-0.049	0.050	0.112	0.084	1.000			
10	Turnover	0.002	-0.030	-0.002	-0.007	0.146	1.000		
11	Employees	0.232	0.160	-0.051	0.192	-0.023	0.586	1.000	
12	Age	-0.126	0.143	0.132	0.043	0.246	0.600	0.207	1.000

*. Number of observations N=37.

**. Turnover values are given in billion US dollars, its N=36.

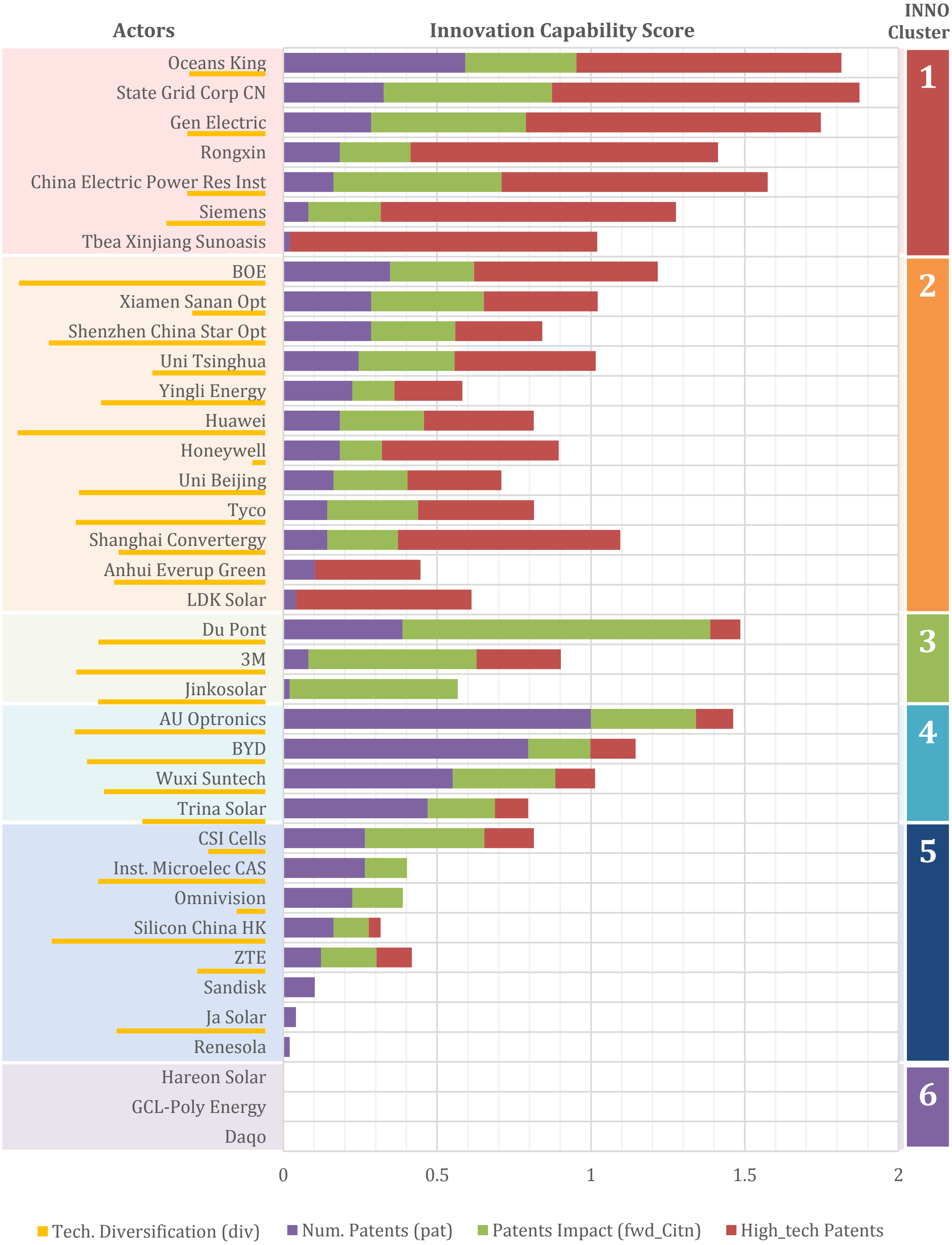
Note: Variables are defined in table 1.

4.2.1 Patterns of Innovation Capability

Considering the quantity, quality and diversity of patenting activities as clustering variables for innovation capability, six clusters were identified. Figure 5 shows the normalized variables for each actor along with the distribution of actors into the resulting clusters.

To check the effectiveness of the analysis in classifying actors according to their innovative performance, Analysis of variance (ANOVA) is used. Furthermore, Tukey HSD post hoc test is subsequently conducted to understand the characteristics of each cluster. Table 3 contains the statistical results of ANOVA analysis and Tukey test for innovation capability clusters (INNO).

Figure 5: Inventive Activity Profiles of the Top PV Innovators in China



Authors’ own elaboration, Data Source: PATSTAT 2015

Table 3: ANOVA and Tukey HSD Analysis for Innovation Capability Clusters

ANOVA Analysis for Innovation Capability Clusters						
		Sum of Squares	df	Mean Square	F	Sig.
pat	Between Groups	2727.791	5	545.558	11.478	0.000**
	Within Groups	1473.506	31	47.532		
	Total	4201.297	36			
fwd_citn	Between Groups	3.355	5	0.671	9.146	0.000**
	Within Groups	2.274	31	0.073		
	Total	5.630	36			
div	Between Groups	6.289	5	1.258	23.612	0.000**
	Within Groups	1.651	31	0.053		
	Total	7.940	36			
high_tech	Between Groups	4.089	5	0.818	73.321	0.000**
	Within Groups	0.346	31	0.011		
	Total	4.435	36			

Post Hoc Test: Multiple Comparisons (Tukey HSD)							
Dependent Variable	INNO (I)	INNO (J)	Mean Diff. (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
high_tech	1	2	.518**	0.050	0.000	0.365	0.670
		3	.825**	0.073	0.000	0.604	1.047
		4	.823**	0.066	0.000	0.622	1.024
		5	.910**	0.055	0.000	0.744	1.076
		6	.949**	0.073	0.000	0.728	1.171
	2	3	.308**	0.068	0.001	0.101	0.515
		4	.306**	0.061	0.000	0.121	0.491
		5	.393**	0.048	0.000	0.246	0.539
		6	.432**	0.068	0.000	0.225	0.639
fwd_citn	3	1	.644*	0.187	0.019	0.076	1.211
		2	.890**	0.175	0.000	0.359	1.421
		4	.775**	0.207	0.009	0.148	1.403
		5	1.052**	0.183	0.000	0.495	1.608
		6	1.277**	0.221	0.000	0.605	1.948
pat	4	1	22.929**	4.321	0.000	9.810	36.040
		2	24.917**	3.980	0.000	12.840	37.000
		3	26.500**	5.266	0.000	10.520	42.480
		5	27.125**	4.222	0.000	14.310	39.940
		6	34.500**	5.266	0.000	18.520	50.480
div	1	6	1.165**	0.159	0.000	0.681	1.648
	2	1	.343*	0.110	0.041	0.010	0.676
		6	1.508**	0.149	0.000	1.056	1.960
	3	6	1.608**	0.188	0.000	1.036	2.180
	4	6	1.570**	0.176	0.000	1.035	2.105
	5	6	1.298**	0.156	0.000	0.824	1.772

Only positive significant mean differences are shown in this table. Definitions of variables are stated in table 1.
*. The mean difference is significant at the 0.05 level.
**. The mean difference is significant at the 0.01 level.

The results show that for all clustering variables, there was a statistically significant difference between INNO clusters as determined by one-way ANOVA at the $p<0.001$ level. The post hoc comparisons, using Tukey HSD test, revealed that high-tech innovations were significantly higher in the first cluster INNO1 compared to all other clusters. INNO2 had also significantly greater high-tech innovations than those of INNO3, 4, 5, and 6. On the other hand, the cluster INNO3 showed statistically significant advantage over all other clusters in forward-citation score. The quantity of innovative activities (number of patent filings) was significantly higher in INNO4 compared to the others. Finally, in terms of technological diversification, INNO6 was significantly lower than all other clusters. INNO1 also had significantly lower diversification than INNO2.

Taken together, these results give better insight into the differences between clusters:

1. **INNO1:** comprises the actors with high-tech speciality.
2. **INNO2:** actors have higher diversity within medium technological sophistication.

Although the remaining clusters are specialized in low-tech, each one of them has its defining characteristic:

3. **INNO3:** actors have patents with high impact (i.e. receiving more forward citations).
4. **INNO4:** actors have high quantity and technological diversity of patent filings.
5. **INNO5:** innovations are low in quantity and quality.
6. **INNO6:** firms did not file any transnational patents in the period of consideration.

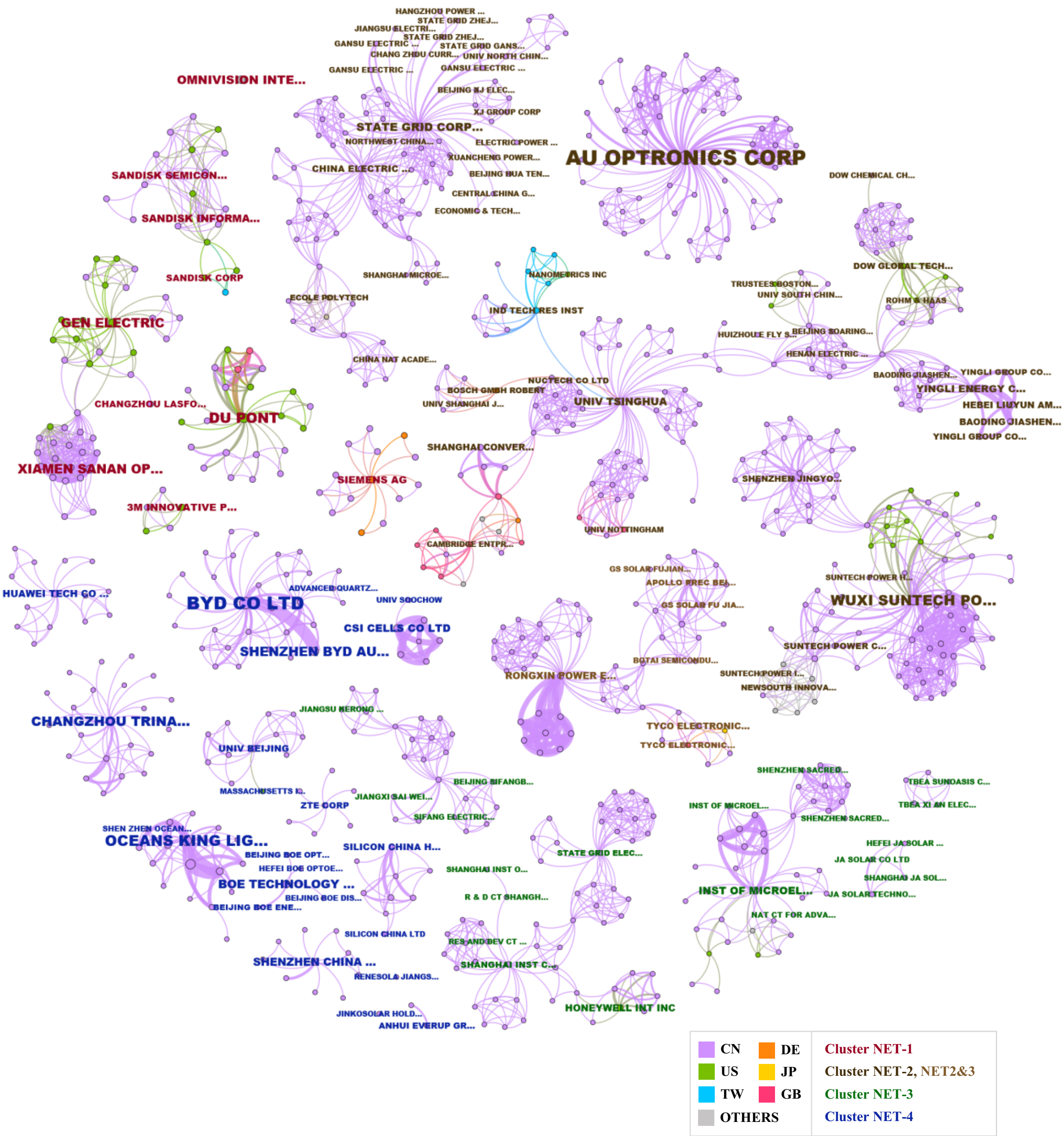
4.2.2 Patterns of Network Embeddedness

The second analytical dimension is built upon network analysis of collaboration in patents. Figure 6 shows a subgraph of co-patenting network of PV in China. It contains the components to which the identified actors of the sample belong. This subgraph represents 35% of the complete network in terms of nodes and 51% in terms of edges. The colour of nodes represents the country where applicants are located.

In this stage a second cluster analysis is conducted, but this time based on network embeddedness variables. The resulting clusters are labelled with NET throughout this paper. Furthermore, node labels in figure 6 are coloured based on their NET clusters. Five NET clusters were identified.

Similar to the procedure done for INNO clusters (section 4.2.1), one-way ANOVA and Tukey HSD test is conducted for NET clusters (table 4). Again, the results show that for all clustering variables, there was a statistically significant difference between NET clusters at the $p<0.001$ level. Tukey HSD test revealed significant advantage for the first cluster NET1 in collaboration with foreigners. On the other hand, actors within NET2 had significantly higher component size, degree, and betweenness centrality than other clusters. Network clustering coefficients for actors in NET3 were significantly larger than those of other NET clusters.

Figure 6: Co-Patenting Network of the Top PV Innovators in China



Subgraph of the co-patenting network of Chinese transnational patents over 1995-2014. 35% of nodes and 51% of edges are visible. Data sources: PATSTAT 2015b; (Dominguez Lacasa & Shubbak, 2018). Authors' own elaboration.

Taken together, these results show:

1. **NET1:** contains actors with high global integration.
2. **NET2:** actors have high embeddedness in the collaboration network as shown by their central positions in relatively large components.
3. **NET3:** fulfils the requirements of small-world networks, given the relatively low degree and high clustering coefficients of its actors.
4. **NET4:** contains actors with low network embeddedness.
5. **NET5:** contains firms that did not file any transnational patents.

Table 4: ANOVA and Tukey HSD Analysis for Network Embeddedness Clusters

ANOVA Analysis for Network Embeddedness Clusters						
		Sum of Squares	df	Mean Square	F	Sig.
deg	Between Groups	11440.301	4	2860.075	9.740	0.000*
	Within Groups	9396.131	32	293.629		
	Total	20836.432	36			
btwn_centr	Between Groups	22669354.315	4	5667338.579	6.025	0.001*
	Within Groups	30100986.107	32	940655.816		
	Total	52770340.422	36			
clust_coef	Between Groups	7.228	4	1.807	26.729	0.000*
	Within Groups	2.163	32	0.068		
	Total	9.392	36			
com_Size	Between Groups	43785.029	4	10946.257	27.703	0.000*
	Within Groups	12644.214	32	395.132		
	Total	56429.243	36			
frgn_coll	Between Groups	0.863	4	0.216	13.921	0.000*
	Within Groups	0.496	32	0.016		
	Total	1.360	36			

Post Hoc Test: Multiple Comparisons (Tukey HSD)						95% Confidence Interval	
Dependent Variable	NET (I)	NET (J)	Mean Diff. (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
frgn_coll	1	2	.307**	0.064	0.000	0.120	0.493
		3	.390**	0.069	0.000	0.189	0.590
		4	.407**	0.058	0.000	0.238	0.575
		5	.413**	0.086	0.000	0.165	0.661
com_Size	2	1	76.411**	10.288	0.000	46.685	106.136
		3	67.292**	10.735	0.000	36.273	98.310
		4	86.510**	8.932	0.000	60.701	112.319
		5	97.125**	13.457	0.000	58.241	136.009
deg	2	1	36.375**	8.869	0.002	10.750	62.000
		3	47.042**	9.254	0.000	20.302	73.781
		4	36.452**	7.700	0.000	14.203	58.700
		5	54.375**	11.601	0.000	20.856	87.894
btwn_centr	2	1	1857.759**	501.958	0.007	407.405	3308.112
		3	1924.116**	523.792	0.007	410.674	3437.557
		4	1900.222**	435.821	0.001	640.963	3159.482
		5	1953.116*	656.608	0.041	55.917	3850.315
clust_coef	1	5	1.426**	0.179	0.000	0.908	1.945
	2	5	1.296**	0.176	0.000	0.787	1.805
	3	1	.439*	0.145	0.036	0.021	0.857
		2	.569**	0.140	0.003	0.163	0.975
		4	.678**	0.128	0.000	0.307	1.049
		5	1.865**	0.184	0.000	1.334	2.396
	4	5	1.187**	0.167	0.000	0.706	1.668

Only positive significant mean differences are shown in this table. Definitions of variables are stated in table 1.
*. The mean difference is significant at the 0.05 level.
**. The mean difference is significant at the 0.01 level.

4.3 Concurrency Analysis

The analysis explained in section 4.2 resulted in clearly discernible clusters for both innovation capability and network embeddedness. However, towards achieving the aim of this research of understanding the confluence of both dimensions on the economic performance, a concurrency matrix of their cross relations is created (table 5).

Having the NET clusters as rows and the INNO clusters as columns[5], the concurrency matrix provides the exact positioning of actors in this two-dimensional space. As shown in table 5, actors can be found in 16 out of the 30 possible combinations in the matrix.

Table 5: Concurrency Matrix - Mapping of PV Innovators in China

	INNO-6	INNO-5	INNO-4	INNO-3	INNO-2	INNO-1	
Many-frgn / Medium / Medium-clustering		Sandisk Omnivision		Du-Pont 3M	X.Sanan-Opt	Siemens Gen Elect	NET1
Med-frgn / Large-size / Medium-clustering			Wuxi-Suntech AU-Optronics		Yingli S.Convertergy Uni-Tsinghua	State Grid CC CEPR Rongxin	NET-2
Few-foreigners / Med-size / S-World		Inst.Micr-CAS Ja-Solar			Honeywell Tyco LDK-Solar	TX-Sunoasis	NET-3
Few-foreigners / Small-size / Low-clust.		ZTE CSI-Cells Si-China-HK Renesola	BYD Trina-Solar	Jinkosolar	BOE S.China-Star Huawei Uni-Beijing Anhui-Everup	Oceans-King	NET-4
No-patents	GCL-Poly Daqo Hareon						NET-5
	No-patents	Few-patents	Many-patents	Few-patents	Medium-patents		
		Low-impact	Med-impact	High-impact	Medium-impact		
		Low-tech			Med-tech	High-tech	

Besides its important use as illustrative tool per se for understanding the nature of actors' technological engagement, the introduced concurrency matrix provides a promising basis for classifying new actors within the system or even for inductively generalizing the classification into other technological fields and systems. Another important application of the matrix is to use it for testing the research hypotheses.

To investigate whether a significant relationship can be found between the identified patterns, concurrency interactions, and economic performance of actors, a two-way multivariate analysis of variance (MANOVA) is utilized having age, size, turnover, and productivity as dependent variables. Table 6 shows the results of Pillai's trace, Wilks' Lambda, Hotelling's trace, and Roy's largest root multivariate tests of the full factorial model of INNO and NET clusters. The results show significant relationships between INNO*NET interaction on the economic performance at the level of $p<0.01$. This result confidently rejects the null hypothesis that the multivariate means of all groups are equal.

Table 6: Results of multivariate tests for INNO*NET full factorial model

Multivariate Tests[a]						
Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**
Intercept	Pillai's Trace	0.936**	61.766[b]	4.000	17.000	0.000
	Wilks' Lambda	0.064**	61.766[b]	4.000	17.000	0.000
	Hotelling's Trace	14.533**	61.766[b]	4.000	17.000	0.000
	Roy's Largest Root	14.533**	61.766[b]	4.000	17.000	0.000
INNO	Pillai's Trace	0.946	1.549	16.000	80.000	0.103
	Wilks' Lambda	0.260*	1.824	16.000	52.573	0.052
	Hotelling's Trace	2.090**	2.025	16.000	62.000	0.025
	Roy's Largest Root	1.656**	8.282[c]	4.000	20.000	0.000
NET	Pillai's Trace	1.151**	2.955	12.000	57.000	0.003
	Wilks' Lambda	0.190**	3.290	12.000	45.269	0.002
	Hotelling's Trace	2.558**	3.340	12.000	47.000	0.001
	Roy's Largest Root	1.585**	7.528[c]	4.000	19.000	0.001
INNO * NET	Pillai's Trace	1.768**	2.263	28.000	80.000	0.002
	Wilks' Lambda	0.046**	3.006	28.000	62.717	0.000
	Hotelling's Trace	6.709**	3.714	28.000	62.000	0.000
	Roy's Largest Root	4.640**	13.257[c]	7.000	20.000	0.000

a. Design: Intercept + INNO + NET + INNO * NET.
b. Exact statistic
c. The statistic is an upper bound on F that yields a lower bound on the significance level.
*. Significant at the 0.1 level.
**. Significant at the 0.05 level.

Inspecting the model for between-subject effects on each dependent variable, table A2 shows a significant effect of innovation-capability on actors' turnover, as well as significant relationships between network-embeddedness, age, turnover and productivity. Similar significant relationships were found between INNO*NET interaction with the dependent variables of age and economic performance. However, no significant effects were found for any of the model elements on firms' size (number of employees).

To clearly illustrate the results and test the research hypotheses, the identified patterns are combined based on their commonalities. This results in three innovation levels:

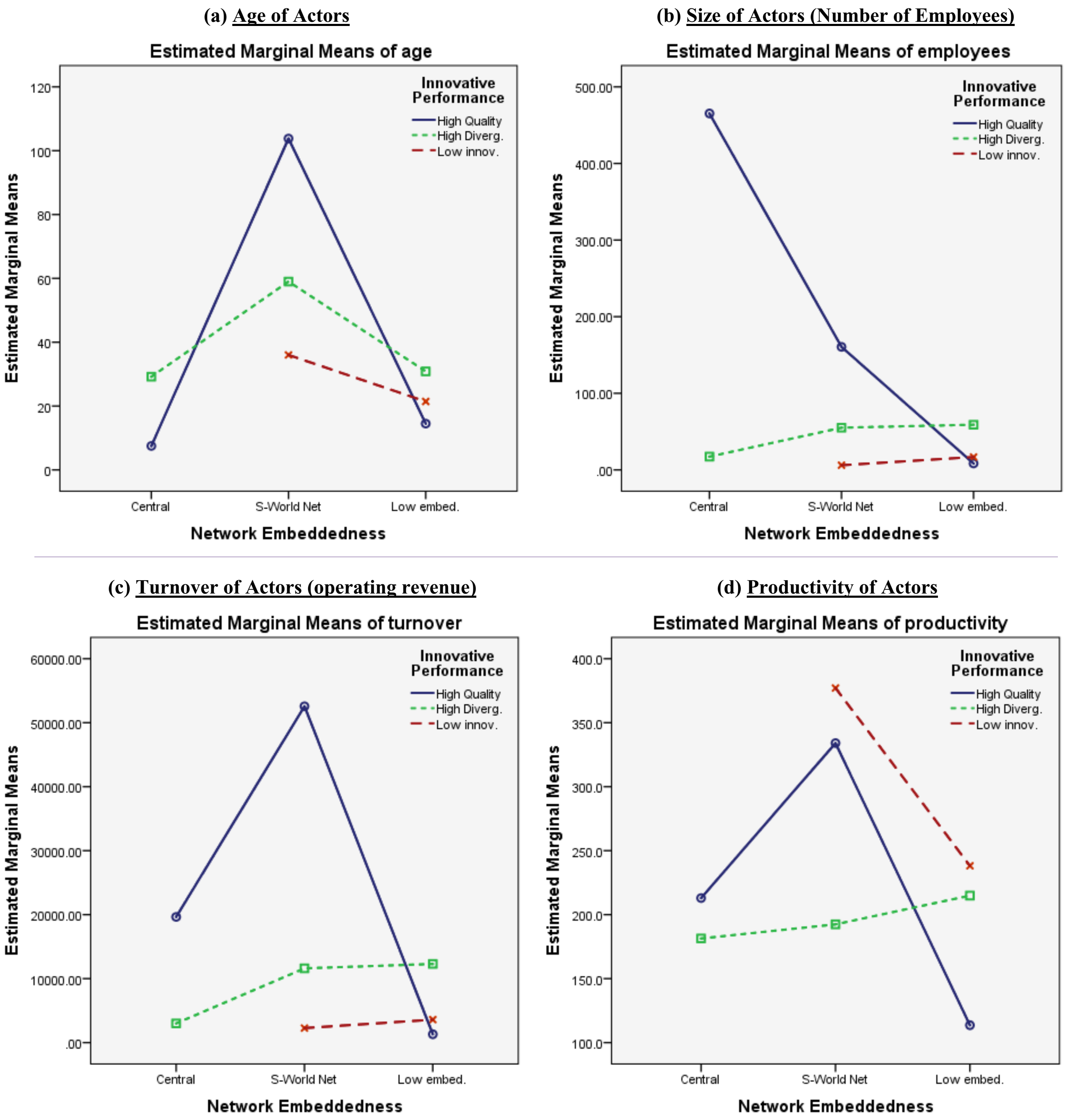
1. **High-quality innovation level:** combines the high-tech and high-impact innovation clusters, INNO1 and INNO3 respectively.
2. **High-diversity innovation level:** combines the diverse med-tech and high-quantity clusters, INNO2 and INNO4 respectively.
3. **Low innovation level:** combines the innovation clusters INNO5 and INNO6.

On a related front, three network patterns are defined as:

A. **High centrality pattern:** contains the highly embedded actors of the cluster NET2.
B. **Small-world pattern:** combines the globally integrated and highly clustered actors of NET1 and NET3 respectively.
C. **Low embeddedness pattern:** combines the network clusters NET4 and NET5.

Figure 7 illustrates the detailed comparisons of dependent variables (estimated marginal means) across the innovation groups and network patterns.

Figure 7: Age, Size, and Economic Performance across Concurrency-Matrix Clusters



Authors' own elaboration.

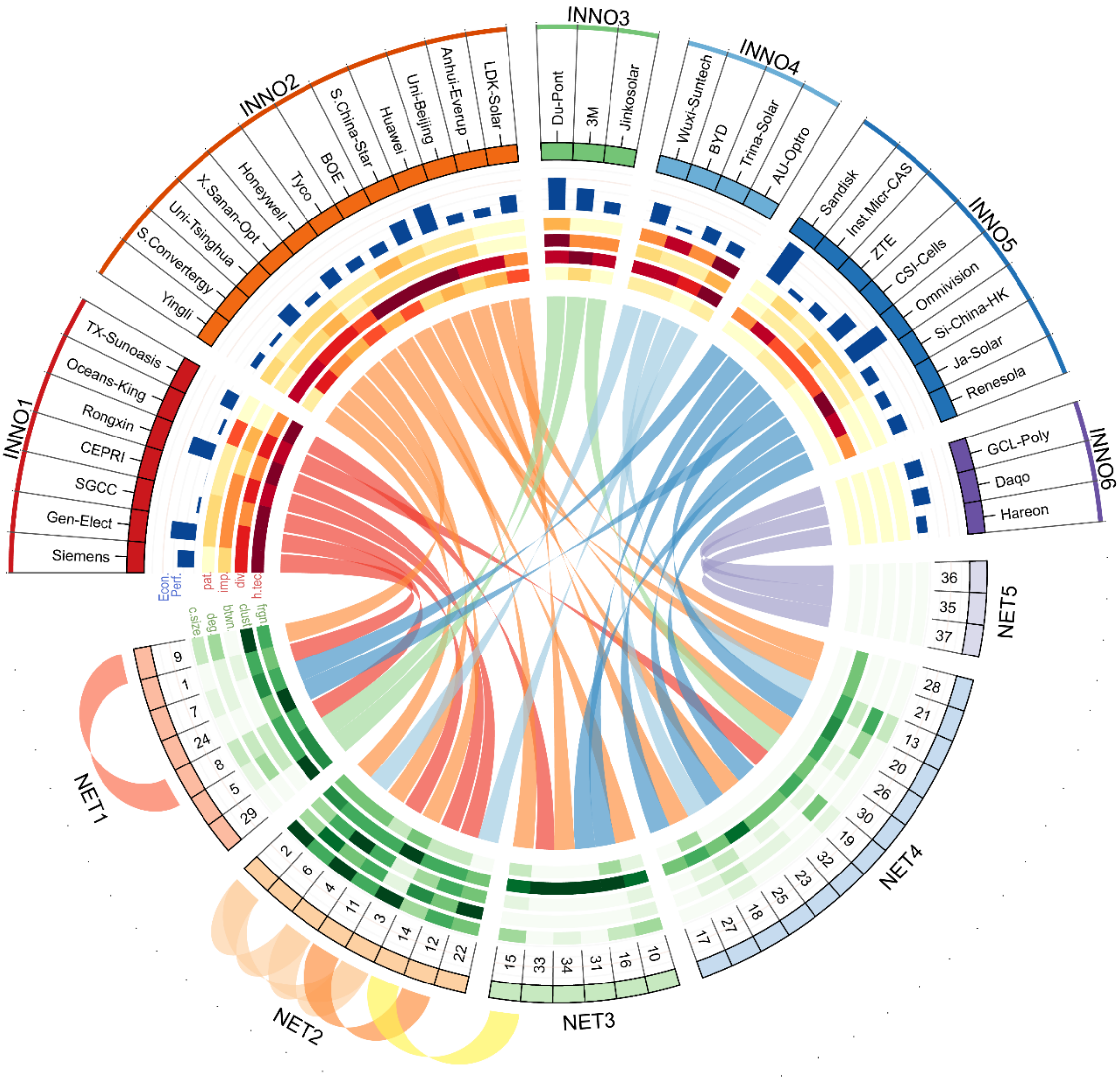
4.4 The complete image

Putting everything together, figure 8 shows the full overview of the main actors within the Chinese innovation system of PV technology. The circular visualization shows actor profiles, clustering variables, resulting clusters, concurrency, and productivity (as an indicator of economic performance).

The upper half of the circle represents INNO clusters, with heatmaps of their clustering variables, as well as a bar chart of economic productivity. The lower half of the visualization represents the NET clusters along with their clustering variables heatmap.

Actors are numbered as in table A1. The central area within the circular graph shows the concurrency relations between the two cluster sets. Finally, co-patenting links are shown in the lower left quarter of the figure. The figure helps better understanding of the results and viewing all the discussed aspects simultaneously.

Figure 8: The Complete Image of PV Innovators in China
Circular Visualization of Clustering, Concurrency, and Economic Performance



Author's own elaboration.

5. DISCUSSION AND HYPOTHESES TESTING

As the main aim of this paper is to disentangle the combined effects of innovation-capability and network-embeddedness on firms' performance, this section discusses the empirical results through testing the research hypotheses introduced in section 2.

According to figure 7c, actors with high-quality innovations and actors with high-diversity have significantly higher turnover than those with low innovation capability. This result supports **Hypothesis 1a**, which stated that *organizations with high innovation-capability are likely to achieve higher economic performance*. This result confirms the large body of literature on the positive economic impact of innovation, such as (Adeyeye, et al., 2013; Andries & Faems, 2013; Hashi & Stojčić, 2013; Silva, et al., 2017).

Although the hypothesis 1a is strongly supported for turnover, a non-significant negative effect can be found for the second indicator of economic performance: productivity (figure 7d), where low innovative actors score higher productivity levels. While such finding sounds contradicted with (Cainelli, et al., 2006), it can be better explained by the fact that such low innovative firms are of smaller size and usually focus on matured technologies and manufacturing of the 'dominant-design', where mass production is more important than R&D for a successful business. This highlights an additional difference between manufacturing and service sectors. However, given this result of a higher productivity scored by less innovative firms, does it mean that the high R&D expenses yields a negative outcome on the overall financial performance of firms within the manufacturing sector? To answer this question a more careful consideration of the economic system is needed. Despite the communist political system of China, its economic system is totally capitalist. Which means that business success is more accurately measured by firms' net profits than productivity. As shown in table A1, the large firms in the Chinese PV sector have on average much larger revenues and profits than small and medium enterprises despite their lower productivity. For such large firms, innovation plays a key role in maintaining their market leadership.

Hypothesis 1b suggested a *positive relationship between firm's age and innovation capability*. The results shown in figure 7a support this hypothesis, as firms with high-quality innovations or high-diversity are relatively older than low-innovation firms. This result further supports the theoretical rationale introduced in section 2.1.

Figure 7b shows positive relationships between firm size, on the one hand, and innovation capability and network embeddedness, on the other. This sound compatible with the literature reviewed in section 2, such as (Wang, et al., 2018), as well as with the **Hypotheses 1c and 2c**, which stated that *larger firms tend to have higher innovation capability and are more embedded in knowledge networks.* However, due to the non-significant MANOVA for the dependent variable 'employees', we cannot confidently accept hypotheses 1c and 2c, nor reject them.

Hypothesis 1d suggested *a higher importance of innovation quality than quantity in influencing economic performance*. The results shown in figure 7 support this hypothesis (only in highly embedded networks), where actors with high-quality innovations achieved higher turnover and productivity levels than those with high-diversity and quantity. This result stresses the significant role of influential process innovations as well as radical product innovations for manufacturing firms to achieve and maintain high economic performance within the technology-based sector of solar PV.

Regarding network embeddedness, figures 7c and 7d show higher economic outcomes for small-world and high-centrality patterns only when innovation quality is high. However, network embeddedness is negatively related with economic performance in the other innovation levels. This yields a partial support of **Hypothesis 2a**, which stated that *the network embeddedness of an organization is positively related to its economic performance*. Additionally, since actors in small-world networks are relatively older than low-embedded firms (figure 7a), **Hypothesis 2b** (stating: o*lder organizations are more embedded in networks*) is supported. These results further confirm the theoretical rationale shown in section 2.2 as well as the findings of (Tsai, 2001; Gilsing, et al., 2008; Dominguez Lacasa & Shubbak, 2018).

Another interesting finding within the network-embeddedness dimension is that organizations belonging to small-world networks achieved even a higher economic performance than those with high vertex centrality. This highlights the greater importance of the network structure than the positions of individual nodes. Although organizations in small-world networks had, on average, less direct ties to other actors, the structure of their network components provided them with high proximity to more actors, albeit indirectly. While Tsai (2001) stressed the role of central network positions in providing organizational units with access to new knowledge developed elsewhere, our results shows that the network clustering structure is even more important as it takes both direct and indirect knowledge paths into consideration.

Finally, **Hypothesis 3** suggested *a higher positive impact of innovation on economic performance when network embeddedness is high*. Figure 7c shows a significant higher turnover for actors with high-quality innovations when they are embedded in small-world networks or when they have central network positions. Therefore, we can confidently accept hypothesis 3. This finding, along with the discussion of hypothesis 2a, support our thesis that the impact of innovation on economic performance of firms is highly heterogeneous across different network-embeddedness patterns. Furthermore, it sheds the light on the network and innovation patterns that yielded high economic performance in the Chinese PV sector.

The analysis revealed another interesting remark regarding the innovative organizations, whose activities are technologically diversified. Such firms tend to achieve higher economic performance when operating in small networks with low embeddedness. Sourcing external knowledge in technological fields beyond the specialization of a company is widely considered among the main motivations of interfirm collaboration. Accordingly, this tendency can be explained by the fact that having a diversified portfolio of technological activities internally, such firms need less external collaborations.

6. CONCLUSIONS

The present research shed light on the technological upgrading of China in PV technology. It analysed the patterns of innovative activities and network embeddedness and their impact on economic performance of leading actors within the Chinese technological system of innovation. Based on several market and patent indicators, the paper identified 37 organisations as the main actors in the system. These few actors, however, have a prominent position in the system as they are accountable of more than 60% of PV production and 41% of PV patenting activities in China.

Moreover, six different patterns of innovative activity were recognized along with five network embeddedness patterns. Introducing the analytical tool of concurrency matrix, the co-evolution of both dimensions was captured. The results showed a significant effect of the interaction between innovation-capability and network-embeddedness dimensions on the economic performance of organisations. Confirming the literature on single-basis effects, the paper came up with additional insights on the confluence of both dimensions.

Furthermore, the results revealed interesting findings regarding the most significant factors in each dimension. The analysis went further than confirming the positive impact of innovation on economic performance. It shows that the quality of innovation outcomes is even more important than their quantity or diversity.

Taken together, the results show that the combination of high-quality innovation, global-integration and small-world networks yields in a significantly higher turnover. Accordingly, the results introduce several managerial and policy implications. At the organizational level, it highlights the importance for directors and managerial units to devote greater attention to qualitative R&D activities, strategic knowledge cooperation, and global integration in order to achieve higher economic performance in the long run. Additionally, at the macroeconomic level, the results suggest some implications for policy makers to consider through innovation policies by supporting the establishment of cross-border collaborations, foreign direct investments, and joint-ventures in order to uphold successful technological upgrading.

Some limitations regarding the lack of involvement of two more elements can be considered as an area for further research. Those are the institutional side of innovation system and the dynamic dimension of network analysis over time.

Overall, the paper attempted to push forward a new field by analysing the confluence of two different dimensions that have long been analysed in single basis. The replication of the research methodology for other technological, national, or regional contexts to test whether similar relationships could be found, would likely contribute to economic and business theories development. Whereas, taking the concurrency aspect into consideration in both management strategies and policy making, clean energy technologies such as PV would reach their ultimate goal of being both competitive and politics independent.

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APPENDIX

Table A1: The Main Actors in PV Technological Innovation System in China

	Actor	Type	Ctry	Est. Yr.	Turnover [mill. $]	Empl. [th.]	TN Pat	Specialization
1	Siemens AG	COM	DE	1847	89,059	351.0	4	electronics
2	Yingli Energy Ltd [a,c]	COM	CN	2006	1,535	14.5	11	c-Si cells
3	Shanghai Convertergy Ltd [c]	COM	CN	2010	3	0.05	7	electronics
4	Uni Tsinghua	EDU	CN	1911	1,850	7.2	12	education, research
5	Du Pont	COM	US	1915	25,268	52.0	19	c-Si, TF, 3G cells
6	Wuxi Suntech Power Ltd [a,c]	COM	CN	2001	621	2.0	27	c-Si cells
7	Sandisk Information Tech.	COM	US	1988	5,570	8.8	5	electronics
8	Gen Electric	COM	US	1892	117,184	305.0	14	electronics
9	Xiamen Sanan Opto Tech.	COM	CN	1993	741	7.1	14	LED, 3G cells
10	Honeywell Int Inc	COM	US	1885	30,000	125.0	9	chemicals, cells
11	State Grid Corp China	GOV	CN	2003	38,286	927.8	16	electricity trans.
12	China Elect. Power Res Inst	INST	CN	1951	n.a.	1.8	8	research
13	BYD Co Ltd	COM	CN	1995	12,252	200.0	39	automobile, cells
14	Rongxin Power Electronics	COM	GB	2012	1,000	2.6	9	energy, electronics
15	Tyco Electronics Co	COM	CH	1941	12,200	75.0	7	electronics, panels
16	Inst. Microelec. CAS	EDU	CN	1928	65	0.8	13	education, research
17	ZTE Corp	COM	CN	1985	12,220	69.1	6	panels, electronics
18	Trina Solar Energy [a,c]	COM	CN	2006	3,036	13.6	23	c-Si cells
19	Oceans King Lighting [c]	COM	CN	1995	136	2.7	29	organic cells
20	Canadian Solar CSI Cells [a,c]	COM	CA	2001	3,468	9.0	13	c-Si cells
21	BOE Technology Group	COM	CN	1993	7,448	42.8	17	display, electronics
22	AU Optronics Corp	COM	TW	2001	11,018	62.8	49	c-Si cells, panels
23	Shenzhen China Star Opt	COM	CN	2009	2,520	7.5	14	electronics
24	Omnivision Tech.	COM	US	1995	1,379	2.2	11	panels
25	Silicon China HK	COM	CN	1992	15	0.1	8	c-Si cells, panels
26	Huawei Tech Co Ltd	COM	CN	1987	59,466	140.0	9	electronics
27	Uni Beijing	EDU	CN	1898	1,290	8.6	8	education, research
28	Anhui Everup Green Energy [c]	COM	CN	2001	27	0.2	5	panels, electronics,
29	3M Innovative Prop. Co	COM	US	1902	30,274	89.8	4	electronics, storage
30	Jinkosolar Co Ltd [a,c]	COM	CN	2006	2,477	14.0	1	c-Si cells
31	Ja Solar Co Ltd [a,c]	COM	CN	2005	2,084	12.6	2	c-Si cells
32	Renesola Ltd [b,c]	COM	CN	2006	1,299	5.4	1	Si-feedstock, cells
33	Tbea Xinjiang Sunoasis [b,c]	COM	CN	2000	1,046	5.0	1	Si-feedstock
34	LDK Solar Hi-Tech Ltd [b,c]	COM	CN	2005	3,490	13.3	2	Si-feedstock
35	GCL-Poly Energy [b,c]	COM	CN	2006	4,546	17.7	0	Si-feedstock
36	Daqo Group Co Ltd [b,c]	COM	CN	1965	2,638	10.0	0	Si-feedstock
37	Hareon Solar Technology [a,c]	COM	CN	2000	933	6.1	0	Poly-Si cells

Actors in this table are sorted according to their appearance in PATSTAT 2015b database.

Actors 1-34 were involved in co-patenting network components accountable for 41% of the Chinese TN patent applications in PV technologies.

[a]. Those seven firms were accountable for 34% of the global c-Si PV cell production during 2010-2015 (60% of the Chinese production).

[b]. Those five firms were accountable for 31% of the global Si-feedstock production during 2010-2015 (more than 90% of the Chinese production).

[c]. The business of those fifteen firms are solely focused on PV energy sector.

Table A2: Two-way MANOVA Analysis for INNO*NET Concurrency

2-Way MANOVA: INNO*NET (Tests of Between-Subjects Effects)						
Source	**Dependent Variable**	**Type III Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
Corrected Model	**age***	4.43E+04[a]	15	2.95E+03	2.179	0.052*
	turnover**	1.90E+10[b]	15	1.27E+09	5.935	0.000**
	employees	5.19E+05[c]	15	3.46E+04	1.466	0.209
	productivity**	5.14E+05[d]	15	3.43E+04	2.942	0.013**
Intercept	**age****	3.72E+04	1	3.72E+04	27.462	0.000**
	turnover**	3.32E+09	1	3.32E+09	15.519	0.001**
	employees**	1.17E+05	1	1.17E+05	4.939	0.038**
	productivity**	1.50E+06	1	1.50E+06	128.515	0.000**
INNO	age	2.53E+03	4	6.32E+02	0.466	0.760
	turnover**	2.96E+09	4	7.40E+08	3.465	0.026**
	employees	1.12E+05	4	2.80E+04	1.186	0.347
	productivity	9.46E+04	4	2.37E+04	2.030	0.129
NET	**age***	1.13E+04	3	3.77E+03	2.778	0.068*
	turnover**	3.57E+09	3	1.19E+09	5.575	0.006**
	employees	6.48E+04	3	2.16E+04	0.914	0.452
	productivity**	1.36E+05	3	4.52E+04	3.877	0.025**
INNO * NET	**age***	1.99E+04	7	2.84E+03	2.097	0.092*
	turnover**	8.42E+09	7	1.20E+09	5.628	0.001**
	employees	2.20E+05	7	3.14E+04	1.331	0.287
	productivity**	2.32E+05	7	3.32E+04	2.847	0.031**
Error	age	2.71E+04	20	1.36E+03		
	turnover	4.27E+09	20	2.14E+08		
	employees	4.72E+05	20	2.36E+04		
	productivity	2.33E+05	20	1.17E+04		
Total	age	1.30E+05	36			
	turnover	2.99E+10	36			
	employees	1.18E+06	36			
	productivity	2.84E+06	36			
Corrected Total	age	7.14E+04	35			
	turnover	2.33E+10	35			
	employees	9.92E+05	35			
	productivity	7.48E+05	35			

a. R Squared = .620 (Adjusted R Squared = .336)
b. R Squared = .817 (Adjusted R Squared = .679)
c. R Squared = .524 (Adjusted R Squared = .166)
d. R Squared = .688 (Adjusted R Squared = .454)
*. Significant at the 0.1 level.
**. Significant at the 0.05 level.

NOTES

[1] See for instance, the decision of US president Donald Trump in June 2017 to withdraw the United States from the 2015 Paris climate agreement and its impact on the federal government plans and policies (Victor, et al., 2017).

[2] From that perspective, the present paper can be considered as an attempt to push this area of research forward by studying the cross interaction between innovation capability and network embeddedness and its impact on economic performance.

[3] To make the forward citation index comparable across patent applications with different priority dates, the number of applications citing a patent is divided by the number of years elapsed since the patent has been filed.

[4] Network indicators are based on (Dominguez Lacasa & Shubbak, 2018), where social network analysis was conducted using Gephi 0.9.1 software (Bastian, et al., 2009). For detailed explanation of network analysis and indicators, see (Jackson, 2008).

[5] The characteristics of network and innovation clusters are shown in the left and bottom sides respectively. The significant feature of each cluster is stated in bold.