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Urban Economic Cluster Template and Its Dynamics of Beijing, China

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Abstract: Economic clusters have been a central focus of current urban and regional research, policies and practices. However, a methodology to identify and analyze policy-relevant economic cluster dynamics is still not well developed. Based on input-output (I-O) data of 1987, 1992, 1997, 2002 and 2007 of Beijing, this article presents an adapted principle component analysis for identifying the evolution of local economic cluster patterns. This research addresses the changes of economic interaction of industries with complementary and common activities over time. The identified clusters provide an insight into the reality of economic development in a diversifying urban economy: the increasing importance of services and the growing interaction between service and manufacturing industries. Our method therefore provides the analysts with a better understanding of the emergence, disappearance and development of economic clusters citywide. The results could be used to assist monitoring urban economic development and designing more practical urban economic strategies.

Keywords: economic clusters; industrial linkages; urban economic dynamics; functional analysis; input-output; Beijing; China

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1 Introduction

Since the late 1990s, Economic Clusters (ECs) have become one of the most prominent phenomena in urban and regional economies and at the centre of urban and regional policy (Porter, 1998a; Wu, 2005; Cortright, 2006; Maskell and Malmberg, 2007). However, as a fundamental issue of cluster studies and related policies, the identification of ECs and their evolution at a city level are less investigated**.** Current studies are mostly focused on the development of a cluster in a particular place, largely insufficiently considering local economic structure and market circumstances. This situation results in that the real development is often less successful than the expected. For example, the M4 corridor in the United Kingdom, the Cité Scientifique Île-de-France Sud in France and the Tsukuba Science City in Japan clearly have had less impact than Silicon Valley in the United States (Hall, 1997). In order to avoid simple imitation or wishful visions, a more careful analysis from the perspective of local economic structure is required. By addressing the industrial linkage during the cluster formation, this article presents an approach to identify the (potential) local and regional cluster patterns and examine the dynamics so as to generating relevant information for improving urban and regional economic policies.

Industrial linkage is a fundamental dimension of clusters. It reflects the way of interactions among a group of industries which share certain production or services activities, and often may imply formal or informal cooperation with respect to labour, knowledge and information. Owing to the economies of scale, it is much more persistent than the firm relationship in regard to agglomeration economies (Midelfart-Knarvik *et al.*, 2002; Rigby and Essletzbichler, 2006). Analysis of

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industrial linkages is also useful for examining local economic structure (Czamanski, 1971; Roepke *et al.*, 1974; Czamanski and Ablas, 1979). Therefore, industrial linkage provides a way for investigating the formation and growth of ECs in local economic structure.

Different configurations of demand and supply interactions produce different types of industrial linkages and therefore different ECs. This paper is interested in deriving ECs by looking at horizontal and complementary linkages. This is because with modern urban economies becoming more complex, diversified and dynamic (Thrift and Olds, 1996; Amin and Graham, 1997), local governments usually play a less important role in strengthening supply chains (vertical linkages) for cluster development. Hence there is no reason for postulating positive correlation between industrial growth and its intensity of linkages to other industries. Weak intermediate trading linkages or low intensity of linkages among industries do not necessarily imply a weak cluster performance (Learmonth *et al.*, 2003). On the other hand, a group of industries with similar demand or supply patterns are more likely to compete for market and resources. Complementary linkages generate mutual attractions between suppliers and users (Hoover and Giarratani, 1999). By stimulating competition and cooperation for market and resources, horizontal relationship facilitates innovation and knowledge spillovers. Such a role is no less than the specialisation process via supply chains (Hertog *et al.*, 2001). Complementary linkages can bring about extra opportunities attracting new suppliers and/or buyers (Malizia and Feser, 1999). The extension of complementary linkages is a process of diversifying the economy for the entire region (Zhang *et al.*, 2013), transferring from the production network to the labour market, and exchanging between very different industries. A common example is the increasing interaction between the manufacturing and service economies.

ECs based upon complementary and horizontal linkages are more meaningful for policy making process, which indicate a favourable environment for the cluster growth. Porter (1998b) argues that current knowledge-driven clustering potentials largely exist in a group of industries with commonalities or complementariness, but unfortunately he does not provide a systematic way for identifying ECs based on such relationships. Industries that are located in the same city may facilitate technological development of other industries through multiple and frequent interactions, which forms a niche that favours cluster germination and growth (Firestone, 2010). The cost of attracting new industries to a city is substantially lower when the new industry has strong technological links to existing industries (Firestone, 2010). Existing businesses and a diverse economic structure form the favourable conditions for new business growth (Rosa and Scott, 1999). Based on the case of Beijing, this paper examines the urban EC template for the development of economic interactions among complementary and common activities, and provides an insight into the economic development in a diversifying urban economy.

2 Materials and Methods

2.1 Study area

Beijing is selected as the study area in this study for testing the applicability of our modified method for identifying ECs and analysing their dynamics (Fig. 1). The municipality presently has 2.069×10^7 inhabitants in 2012 and covers an area of around 16 411 km^2 (Beijing Statistical Bureau, 2013). Since the 1980s, Beijing has been experiencing the transition from a planned economy to a market economy. During this period, there has been dramatic economic restructuring, indicated by the services economy surpassing manufacturing as the dominant sector in the mid 1990s as measured by the share of GDP and employment in the whole economy (Beijing Statistical Bureau, 2013). As a very dynamic city, Beijing provides a good case for investigating urban EC template and its evolution.

2.2 Data source

The data used were Input-Output (I-O) accounts of Beijing for the years of 1987, 1992, 1997, 2002 and 2007 at 2-digit level, provided by the Beijing Statistical Bureau[①]. There are 26, 22, 31 and 40 service industries in the

① The dataset is so far the complete I-O record of Beijing. The full I-O survey was started in 1982 in Beijing and is carried after each five year. Owing to the complexity of the survey and the data system, it is normally released 2–3 years later than that is surveyed, i.e., the latest data so far is 2007 data and the data of 2012 is expected to be published in 2014.

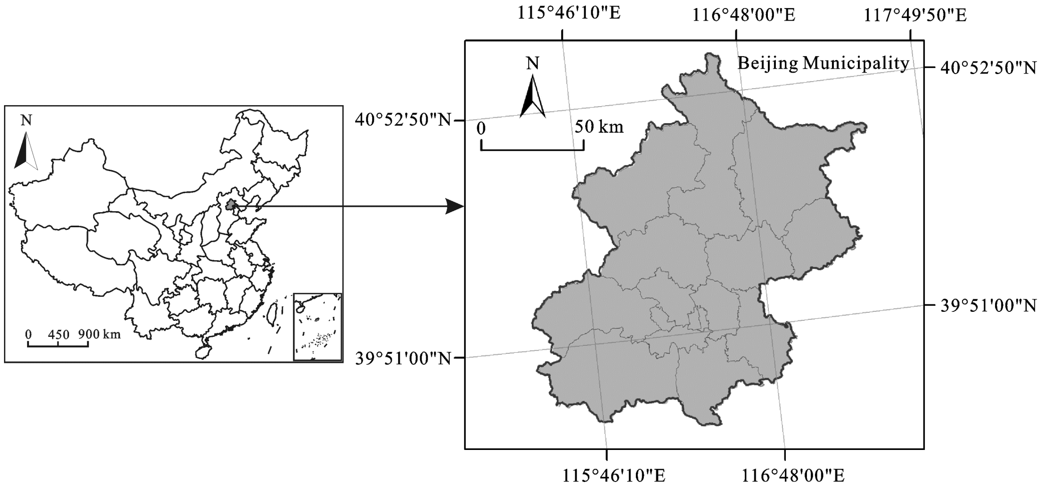

Fig. 1 Location of study area

years of 1987, 1992, 1997 and 2002, and 79 manufacturing industries in each examined year aforementioned. As regards the 2007 data, 87 manufacturing and 40 service industries were included.

2.3 Revised Principal Components Analysis method

The technique of Principal Components Analysis (PCA) has been employed to identify ECs (Streit, 1969; Czamanski, 1971; Roepke *et al.*, 1974). An advantage is that it reveals hidden dimensions underlying a raw dataset. Based on the work of Czamanski (1971) and Feser and Bergman (2000), PCA has been proven successful in terms of finding complementary and horizontal relationships, tracing the network of interactions and revealing critical links in industrial subsystems (O hUallachain, 1984). It offers a relative robust and uniform means of revealing industrial linkages and technological structures, which gives a good indication of the formal and informal channels that foster a positive development of clusters (Feser and Bergman, 2000). More importantly, PCA discloses a group of industries sharing the same or complementary demand or supply patterns so that the cluster configuration represents potential strengths, underlying weaknesses, latent threats and new opportunities (Feser, 2001).

However, PCA still has a potential for improvement. First, to date all research utilizing PCA focuses on manufacturing industries (Feser and Bergman, 2000; Liang *et al.*, 2005; Akgungor, 2006; Funderburg and Boarnet, 2008). This is not compatible with the increasing importance of services and the interactions between services and manufacturing, particularly in China (Si *et al.*, 2013). Second, the work of this type usually derives a rather large number of clusters, which is hard to manage and easily confuses policy analysts. Third, such research is often restricted to a single time slice, which is problematic for a strategic policy oriented application. This limitation can be partially solved by conducting time series analyses (or multi-periodic analysis). Given these concerns, the following adaptations for PCA were proposed.

Adaptation 1: Separate template of manufacturing and service clusters

Two separate PCA analyses were performed for the manufacturing and service clusters respectively. Each process produced one template in different periods. These templates were used to investigate the cluster composition in details.

Adaptation 2: Aggregate template of manufacturing and service clusters

Adaption 1 reveals that the number of manufacturing is two to three times larger than that of service in the dataset while the bulk of the information, in terms of outputs, is concentrated in relatively few industries. PCA equally weights all cases, and therefore it is very likely to underestimate service industries. Particularly, the large number of rather small manufacturing industries obscured the results of analysis. Porter (1990) argues that normally growth potential is presently in only a limited number of industries. Therefore, a generalised local cluster pattern can be revealed by focussing on the relationships among these key industries. A key industry was selected based on its economic significance, by comparing its output with the average for all industries.

Largest industries (M_1): if $x_i>x_t$ for manufacturing industries, or $x_i>x_s$ for service industries;

Large industries (M_2): if $x_t>x_i>x_m$ for manufacturing industries, or $x_s>x_i>x_t$ for service industries;

Small industries (M_3): if $x_i<x_m$ for manufacturing industries, or $x_i<x_t$ for service industries (1)

where x_i is the output value of industry i; x_t is the average output in the whole economy; and x_m and x_s are the average output of all manufacturing, services industries respectively. Because the average sectoral output in the manufacturing economy is lower than in the services economy ($x_m<x_t<x_s$), the membership of industries was cross assigned. This classification weighted the importance of industries relative to their manufacturing or service economies and to the economy as a whole. All key manufacturing and services industries were thus included in PCA to generate aggregate cluster templates. The PCA method for deriving ECs included the following three steps:

Step 1: technical coefficients

$$p_{ij}=\frac{a_{ij}}{\sum_j a_{ij}} \quad , \quad s_{ij}=\frac{b_{ij}}{\sum_j b_{ij}} \tag{2}$$

where a_{ij} represents the purchase value of goods and services of industry i from industry j; b_{ij} denotes the sale value by industry i to industry j; p_{ij} and s_{ij} are intermediary purchase and sale coefficients of industry i from or to industry j, representing its strength of backward and forward linkages.

Step 2: structural similarity of industries

$$m_{lk}= \max\{r_{\mathrm{PP}}(P_l,P_k),r_{\mathrm{PS}}(P_l,S_k),r_{\mathrm{SS}}(S_l,S_k),r_{\mathrm{SP}}(S_l,P_k)\} \tag{3}$$

where P_l, P_k, S_l *and* S_k are the vectors of purchase and sale coefficients for a pair of industries l and k. By measuring the correlation between their technical coefficients, r_{pp}, r_{ss}, r_{ps} and r_{sp} denote purchase similarity, sale similarity, purchase-sale similarity and sale-purchase similarity between the industries l and k. The purchase and sale similarities reflect the horizontal relationships; the purchase-sale and sale-purchase similarities are indications of complementariness. The maximum value m_{lk} of these four structural similarities represents the most important relationship, as variables for the PCA process.

Step 3: generating clusters by means of PCA

PCA was performed using SPSS 15 package. The factors were derived from the eigenvalue on less than 1 and the component matrix was used to interpret the ECs. Referring to other related research (Roepke *et al.*, 1974; Feser and Bergman, 2000; Liang *et al.*, 2005; Akgungor, 2006), the factors were rotated by the Varimax method for improving the interpretability, while variables with factor loadings no less than 0.4 were selected for interpretation.

3 Results and Analysis

3.1 Comparison of separate and aggregate approaches

Table 1 summarises the results of the modified PCA. The separate templates were composed of 14–19 manufacturing clusters and 5–8 service clusters in 1987, 1992, 1997, 2002 and 2007, respectively. The total variances explained were at least 83.7% for manufacturing and above 87.5% for services.

The aggregate templates consisted of 8 to 11 clusters and explained at least 84.6% of the variances. In the first two periods, the numbers of manufacturing industries were much larger, as Beijing had not made the transition from being a manufacturing-dominated to a service-dominated economy. Table 1 also shows that the economic output was very much concentrated in some key industries. Roughly 20%–30% of the number of the manufacturing industries accounted for 75%–79% of the total manufacturing output; 50% of the service industries contributed to 85% of the total service output. The aggregate templates therefore captured the main structure and changes of the Beijing economy.

The results of the separate and aggregate exercises were comparable with respect to components matrices (factor loadings) and communalities. Component matrices are an important indicator for interpreting factors (clusters) based on the relative importance of factor loadings. The picture was in general quite the same for these two approaches, namely separate and aggregate. Therefore, similar interpretations were derived for the clusters generated. As regards the communality, which measures the total explained information of the variables (industries), the aggregate approach effectively improves the statistical explanation for the key industries as compared to the separate approach. For example, in 2002, the communalities for the industries of software and professional technical services increased to 0.89 and 0.98 from 0.66 and 0.67 respectively. The other com-

Table 1 Summary of PCA analysis and extracted clusters of separate and aggregate templates

	1987	1992	1997	2002	2007
Separate template					
Manufacturing					
Number of manufacturing industries	79	79	79	79	87
Number of manufacturing clusters	14	19	19	17	18
Total explained variances in PCA (%)	87.9	91.3	89.0	84.4	83.7
Services					
Number of service industries	26	22	31	40	40
Number of service clusters	6	5	5	7	8
Total explained variances in PCA (%)	93.6	98.0	91.1	89.6	87.5
Aggregate template					
Number of key manufacturing industries	25	22	21	21	17
Account for total manufacturing outputs by key manufacturing industries (%)	74	73	75	79	77
Number of key service industries	12	10	17	19	19
Account for total service outputs by key service industries (%)	82	87	95	84	89
Number of aggregate clusters	9	11	10	9	8
Total explained variances in PCA (%)	89.2	90.6	91.5	90.9	84.6

munalities improved included those for education, health care, oil and pharmaceutical products. Only the automotive industry and manufacturing of other electric machinery and equipment were significantly less 'explained' in the aggregate approach. This is related to the industrial changes at that time, as reflected in the growth of automobile industry and other structural changes in manufacturing.

Take the result of 2007 as an example, Fig. 2 illustrates the relationship between the results of these two iterations. Linkages between two types of clusters were drawn based on the key industries that they share. All clusters were sorted in descending order according to their explained variances of the factors. To some extent, bigger variances (the number 1 in the bracket) mean the bigger share of derived clusters (factors) in the local economic structure, and bigger output value (number 2) indicates the economic significance of the clusters. Clearly, as compared to the separate approach, the aggregate approach condenses the information about the configuration of the clusters and makes the quantitative results more transparent for interpretation and understanding. It provides a concise insight into the main economic dynamics. Some large clusters contained several sub-clusters, such as the cluster of Equipment manufacturing, Construction & Mobile, and the cluster of ICT services in 2007. Some clusters without key industries were not identified in relations to the clusters in the aggregate approach. More importantly, the aggregate approach discloses the link and interactions between manufacturing and services, such as the ICT services and Medical clusters, which gives a clue for investigating the interaction of manufacturing and services in development.

It is worth noticing that some clusters derived from the separate approach did not show up in the aggregate cluster composition because they had no key industries with factor loadings higher than the threshold of 0.4. After checking all component matrices, it shows that all key industries passed the selection criteria for participating in the statistical analysis, which partially confirms the proposition that key industries substantially contribute to the cluster forming. There are few changes about the industries in 1987–2007, which however do not affect the function of the PCA method on identifying the clusters by looking at the latent structure among variables (industries). The differences between the separate and aggregate approaches were checked for each period. The clusters in the separate approach that do not show up in the aggregate template can be categorised as: 1) dwindling activities, such as mining in 1987, construction material-related activities in 1992 and 1997, meat processing and non-ferrous mining & transportation equipments in 2002; 2) industries that did not have a strong position in the urban economy, such as the business and warehousing, civic engineering, and postal services in 1987; 3) recently emerging industries such as sports and entertainment products (related to 'other textile') in 1997 and 2002, and tourism and exhibitions in 2002; 4) industries affected by factors that are hard to interpret, like the combination of beverages, cement, and machinery for electronic appliances in 1992, auto-

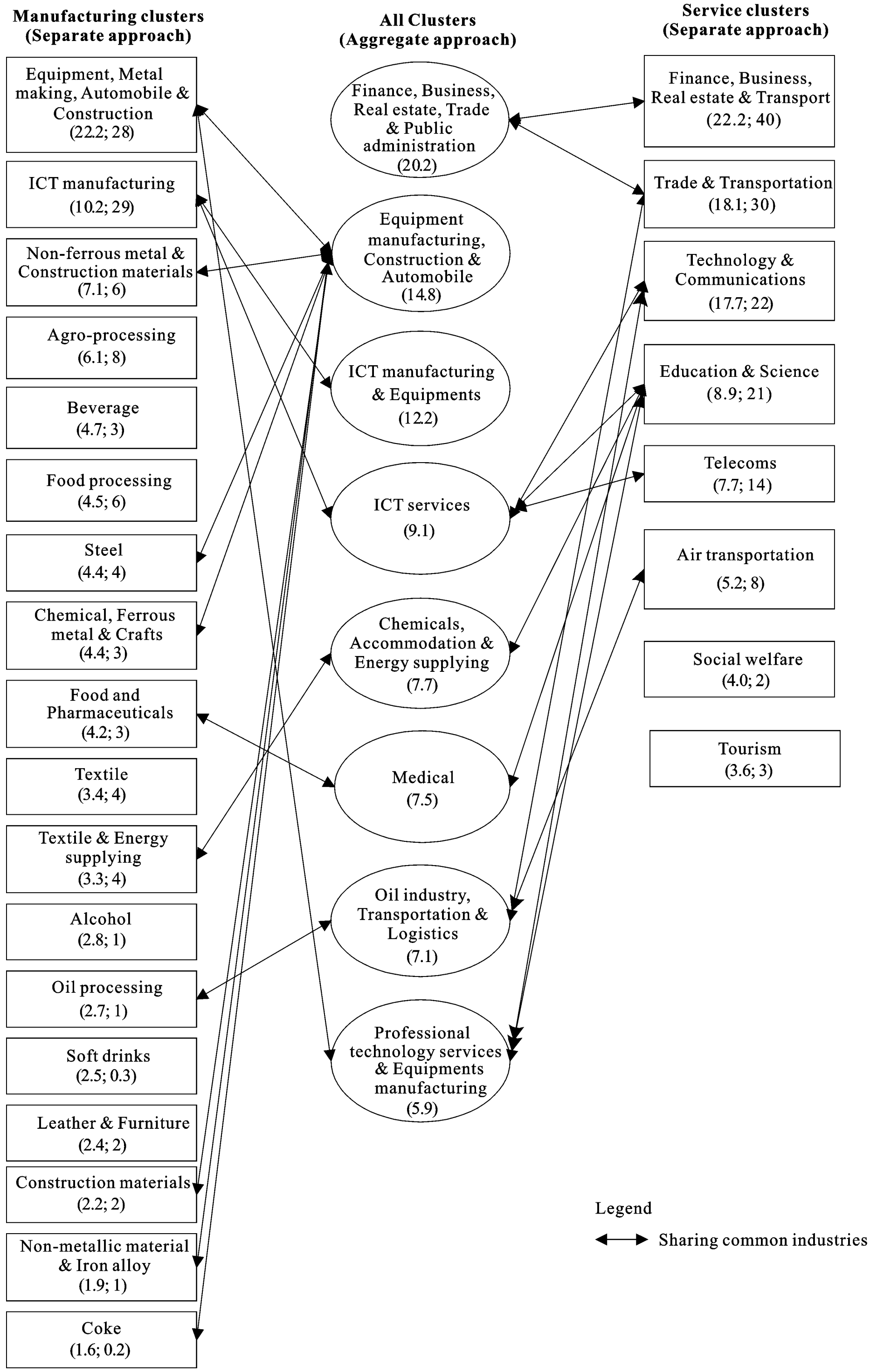

Fig. 2 Relations of derived clusters between separate and aggregate approaches. (number 1, number 2): number 1 represents the variance explained, and number 2 is the share of the output value of the whole manufacturing/services; the aggregate approach only shows the explained variance

mobile-related industry, and machinery-repairing and farm chemicals in 1997. The aggregate approach did rule out some less important clusters, but it also ignored some clusters with small but fast growing industries like the tourism and exhibition cluster in 2002. In 2007, although tourism appeared as a cluster in the separate template, it was not identified by the PCA approach (Fig. 2 was illustrated as an example to show this comparison in 2007).

3.2 Aggregate approach and urban economic cluster template

The aggregate approach provides a generalised and transparent insight into the developments of main clusters and the city′s economic dynamics. Table 2 gives an overview of the main PCA-generated clusters, including their names and their contributing classes of economic activity.

Based on this list, a generalised schematic overview was designed for the main structure of clusters and its changes over time (Fig. 3). This scheme makes it easier to grasp what major economic changes happened that can be used to disseminate the key messages to policy makers. With the number of key industries indicating the size of the clusters (the circle on Fig. 3), the clusters derived from clustering key industries were projected along a time line. The clusters were also positioned along a vertical axis using the commonly defined subdivisions of the economy. Industries contributing to different clusters were illustrated by the connection lines between the clusters.

The connections between the clusters were based on the membership and the factor loadings of industries. Although for the separate and aggregate PCA-analyses, only the key industries were taken into consideration for compiling the generalised cluster pattern. A stricter

Table 2 List of industries for each conceptualized cluster

Type	Conceptualized clusters	Industry
Service	Finance, Insurance, Real estate & Business (FIRE)	Finance, Business, Real estate, Property management, Transport related industries*, energy supply related industries*
	Culture & Information (EI)	Culture, arts & broadcast, Advertisement, Information communication services, Telecommunications, Technology communication and services
	Education & Sciences (ES)	Education, Scientific research & development, Professional services, Technical services
	Public services	Public services, Other social activities services, Personal and household activities
	Public administration	Public administration
Manufacturing-service	Information & Communication technology (ICT)	Manufacturing of computers, Manufacturing of computer parts, Manufacturing of measuring, testing, navigating and control equipment; Watches and clocks, Manufacturing of electric equipments & devices, Manufacturing of other electric machinery and equipment, Manufacturing of communication equipment, Manufacturing of electronic components, Manufacturing of consumer's electronics, Other electronic & communication products, Information communication & service, Computer related services, Software
	Health care & Pharmaceuticals (HCP)	Pharmaceuticals, Health care, Professional services
	Food and Accommodation	Food products or processing, Food and beverage services, Manufacturing of maple food & forage, Manufacturing of alcohol & beverages, Butcher & meat processing, Accommodation
Manufacturing	Petrochemical	Oil industry, Basic chemical materials, Chemosynthetic materials, Other non-metallic mineral products, Manufacturing of petroleum products, Manufacturing of organic chemical products, Manufacturing of plastic products,
	Printing & Paper-products	Printing and reproduction of recorded media, Manufacturing of paper products
	Textile & Wearing apparel	Wearing apparel, Cotton textiles, Woollen textiles, Sewing
	Automobile & Logistics (AVL)*	Automobile, other transport-related industries
	Manufacturing of Machinery & Metalworking (MMM)	Metalworking, Manufacturing of (other) special machinery, Manufacturing of (other) general equipments, Manufacturing of other electric machinery & equipment, Steel processing, Electricity supplying, Manufacturing of boiler, engines & turbine, Manufacturing of other machinery products, Steel and iron related industries, Manufacturing of industrial equipment
	Construction	Construction, Construction materials
Other*		Air passengers Air cargos, Land transportation for passengers and freight, Energy supplying (including electricity, steam, gas and air conditioning supply)

Notes: *Transport-related industries were considered as the cluster of Automobile & Logistics if associated with the Manufacturing of automobile, otherwise as members in other cluster in our case. Energy supplying was contingent on it major host cluster which can be FIRE, Manufacturing of Machinery & Metalworking or Petrochemicals.

structural similarity was applied to derive conceptualized clusters and cluster connections. For the scheme in Fig. 3, industries with factor loadings no less than 0.8 were considered to be determining the nature of the clusters. The interconnections were taken into consideration when industries also had factor loadings of at least 0.4 with the second or third cluster. For example, in the aggregate template of 2002, the cluster of Finance, Insurance, Real Estate & Business (FIRE) had 7 key financial and business industries, of which 5 industries had a factor loading greater than 0.8. Yet, in the same component, accommodation, belonging to the

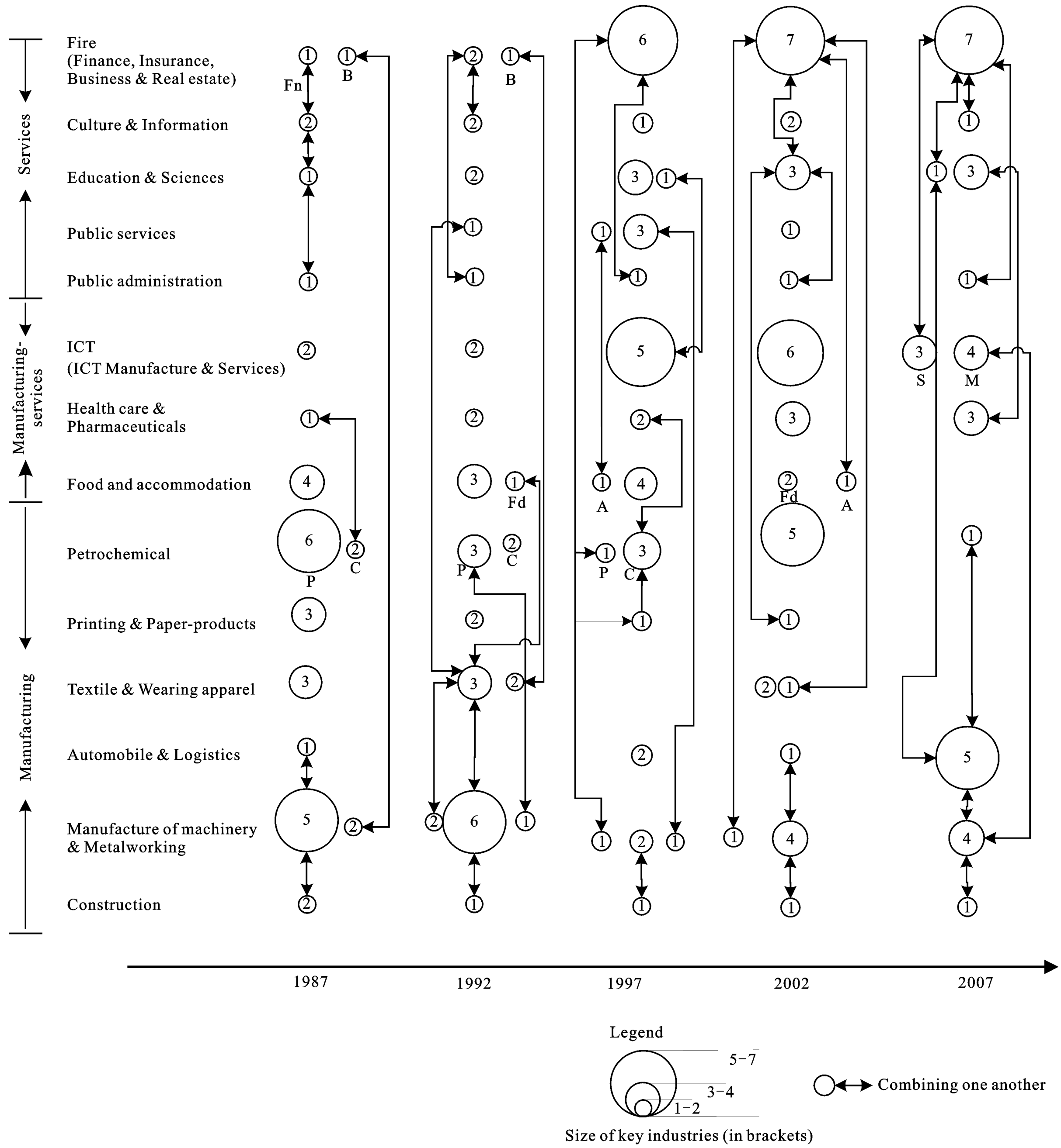

Fig. 3 Schematic overview of economic cluster pattern evolution. Fn, Finance sub-cluster; B, Business sub-cluster; S, Sciences sub-cluster; P, Petroleum sub-cluster; C, Chemical sub-cluster; Fd, Food processing sub-cluster; A, Accommodation sub-cluster; M, ICT manufacturing sub-cluster; S, ICT services sub-cluster. Automobile & Logistics are designated only with the appearance of automobile industry; the transport-related industries are regards as basic supportive activities otherwise. Some clusters were identified as several sub-clusters in some periods for instance FIRE, ICT, Food & Accommodation, and Petrochemical, and Manufacture of Machinery & Metalworking.

Food and Accommodation, was considered to be linked to the FIRE with the factor loading of 0.83. On this basis, a generalised and conceptualised cluster template was derived.

4 Discussion

This overview of cluster dynamics clearly shows the main structural changes of the Beijing economy over the past decades. The rise of service industries and the decrease of manufacturing, in a relative sense, were the key trends. The scheme further elaborates this shift by showing how ECs were developed with respect to composition and inter-linkages. For example, in 1987 the city economy was clearly dominated by manufacturing, particularly the two clusters engaged in processing metals and making machinery (Metalworking and Heavy machinery and Non-ferrous metal processing and Electronic machinery). These clusters were also related to the Automobile cluster. Petrochemicals formed a large cluster comprising six major industries. Other important clusters included Food & Accommodation, Textile & Wearing Apparel, and Printing & Paper-products. At that time, the finance, business services and other service activities were at a very preliminary stage of development, with weak relationships with the cultural, information and education industries. After 1997, particularly in 2002 and 2007, a major transformation occurred with the prominent emergence of the ICT and FIRE clusters which involved complex linkages with other economic activities. The template also shows that in 2007 there was a diversification of Education and Sciences (ES) cluster as a support for the development of FIRE, Automobile and Logistics, and Health care & Pharmaceuticals.

With an ability of interpreting these results in a prospective way, the scheme suggests that the most important clusters for Beijing′s economic future are Information & Communication Technology (ICT), Finance, Insurance, Real estate & Business Services (FIRE), Education & Sciences (ES), Manufacture of Machinery & Metalworking (MMM), Health care & Pharmaceuticals (HCP), Public administration (PA) and Automobile & Logistics (AL). These clusters have been the main driver of Beijing economic growth and evolution.

The cluster evolution template also shows the trade connections among clusters. These interrelationships need close attention when EC strategies are being developed in the future. The changing interconnections can inspire meaningful deliberations. For instance in 1997, accommodation was connected to public services with an increasing number of visitors to the city. In the same year, energy distribution was combined with the FIRE and ES clusters, indicating an important change of major service industries becoming important consumers of energy. In 2002, the steel-making and wearing apparel industries had a connection with the FIRE cluster, which indicated an increase in outsourcing transactions caused by the upgrading wearing apparel industry, as well as increasing import and export transactions for minerals and iron products. The general trend of growing interrelations between the manufacturing and service industries reflects the increasing complementariness of these economic activities. With the rapid growth of service economy in Beijing, modern services are also becoming more important for upgrading some traditional manufacturing industries. This type of deliberation is helpful when investigating the processes of technological upgrading and innovation, and useful for urban economic policy making process.

5 Conclusions

This research presents an adapted PCA based methodology and a new visualisation tool for analysing the dynamics of economic clustering for urban economy. This method investigates the horizontal and complementary linkages among industries in order to provide information for strategic urban economic decision-making. Two adaptations are employed to delineate the industrial structure of the economic clusters and to investigate manufacturing-services interactions during the formation of clusters. Such efforts can improve the understanding of the economic clusters in the context of local economic matrix.

The case study of Beijing, in which the cluster patterns for the period of 1987–2007 were analysed, showed that this methodology is able to reveal the key components of economic transition, which is comprehensible for policy analysts and decision makers. Therefore, a step forward could be made in developing an instrument for urban economic planning support. Different from previous work, this research contributes to the current literature by developing an improved methodology for identifying emerging clusters in a diversifying, service-oriented urban economy. The purpose of this research is not to select 'winners', as is common in traditional I-O analysis, but to detect interrelations among industries as one of necessary factors that create favourable conditions for future economic growth. Periodic analysis allows for investigating the dynamics and trends of ECs citywide to support better and reasonable initiatives and measures in the policy making process.

The research shows that services are increasingly important for the clustering patterns of urban economy in Beijing. More importantly, it shows that the interactions between manufacturing and services are crucial for creating economic opportunities. For instance, the steel industry and wearing apparel are connected to the FIRE industries, implying the upgrading and transformation of both industries. Such interactions are one of the key drivers of manufacturing upgrading, and should be noted and leveraged in current economic plans. There are also some difficulties in interpreting the results. This is partly due to the problems with the comparability I-O tables in the time series, and partly due to the methodological refinements in filtering out meaningful industrial relationships. Another limitation of this improved method is that it is not sensitive to recently emerging clusters. For instance, tourism was not identified in the clustering patterns. This limitation can be overcome by exploring the latest developments through an analysis of current economic indicators or by surveying key stakeholders in the business community. A problem with the I-O type analysis is that clusters are sometimes like industrial classification codes. I-O research for the identification of ECs is also too preliminary. An analysis of knowledge transfer and financial flows needs to be followed up in order to investigate and reflect the linkages and their changes as revealed by the cluster templates.

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