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Knowledge Diffusion within the Datang Sock Manufacturing Cluster in China

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ABSTRACT: In this paper a cognitive community-based analytic framework is established to investigate intra-cluster knowledge diffusion. The results from both a case study on a sock manufacturing cluster in China and an agent-based simulation indicate that the initial pattern of knowledge distribution has a significant impact on the process of knowledge diffusion in a cluster. A cluster with a higher knowledge level but lower knowledge heterogeneity enjoys higher efficiency of knowledge diffusion.

KEY WORDS: Knowledge diffusion; Cluster; Case study; Simulation; China

JEL CODES: R11

(2) INTRODUCTION

Intra-cluster knowledge diffusion has long been recognized as an important source of the competitiveness of industrial agglomeration (MARSHALL, 1920; MASKELL and MALMBERG, 1999; MASKELL, 2001a, 2001b; BRESCHI and LISSONI, 2001). The research on this topic has used two alternative perspectives – geographic proximity and non geographic proximity (GERTLER, 2003; BOSCHMA, 2005). The geographic proximity perspective argues that tacit knowledge can only be transferred by face-to-face interactive learning. The closer two firms are located, the more effective the tacit knowledge transfers, so that a cluster is efficient in knowledge absorption and creation (DESROCHERS, 2001; PORTER, 1990; JAFFE et al., 1993; FLORIDA, 1995; AUDRETSCH and FELDMAN, 1996; MASKELL and MALMBERG, 1999; TALLMAN et al., 2004). On the other hand, the non geographic proximity perspective stresses the effect of relational or social proximity on knowledge diffusion between firms. It argues that as firms in a cluster have a certain type of relational proximity, they can communicate knowledge efficiently between them (CAPELLO and FAGGIAN, 2005; CREVOISIER, 2004; KEEBLE and WILKINSON, 1999).

Though these two perspectives lay a concrete foundation for an understanding of regional diffusion of knowledge, one problem is that they consider meso-level variables only and are unable to explain the uneven diffusion of knowledge in a cluster effectively. This may be the reason why scholars have recently started examining the role of some micro-level variables of firms in knowledge diffusion

（BOSCHMA and WAL, 2006; OWEN-SMITH and POWELL, 2004; GIULIANI and BELL, 2005; GIULIANI, 2005）.

Focusing on the knowledge structure, one of the firm-specific variables, this paper aims to examine the phenomenon of knowledge diffusion within Datang, a sock manufacturing cluster from the Yangtze River Delta, China. Methodologically, we combine a cross-section case study and a longitudinal simulation to investigate both the static and dynamic nature of technological and business knowledge learning and diffusion within a cluster.

YIN (2003) suggests that case studies should start with theoretical propositions. In the next section, we establish a cognitive community-based analytic framework for intra-cluster knowledge diffusion by using the concept of scheme from social cognition. It argues that a cognitive community formed through the cognitive proximity between firms is the fundamental method of knowledge diffusion in the cluster, so that only those firms with similar knowledge structures would be efficient in learning and transferring knowledge.

In section 3, the evidence from our case study of 8 firms indicates that the technological knowledge distribution in Datang is relatively homogeneous (i.e. firms belong to a proximate cognitive community), and hence there is fluent and efficient local learning and diffusion of such knowledge. On the other hand, business knowledge distribution is heterogeneous, and such knowledge diffusion is rare.

Our analytical framework is tested and confirmed not only by the case study, but also the simulation as presented in section 4. This simulation shows that the initial pattern of knowledge distribution has a significant impact on the process of knowledge diffusion in a cluster. A cluster with a higher knowledge level but lower knowledge heterogeneity enjoys higher efficiency of knowledge diffusion. In section 5, we summarise our findings and discuss the implications as well as limitations of this study.

2. THEORETIC FRAMEWORK

It is generally accepted that the efficiency of intra-cluster knowledge diffusion is very important for the competitiveness of a cluster. Knowledge diffused in a cluster is often classified into two categories: tacit or codified (MASKELL, 2001a; PINCH et al, 2003). According to this classification, two alternative perspectives, geographic proximity and non geographic proximity, have emerged. Although these perspectives emphasise the different factors influencing intra-cluster knowledge diffusion, they both have an implicit assumption that firms in a cluster are homogenous, and what determines the efficiency of knowledge diffusion among firms is the similarity of some meso-level variables such as geography, culture and relationship (BOSCHMA, 2005).

It has recently been realised that some micro- or firm-specific variables also play a critical role in intra-cluster knowledge diffusion. For instance, OWEN-SMITH and POWELL (2004) emphasise the influence of a firm’s social role in knowledge diffusion in a cluster. GIULIANI (2005), GIULIANI and BELL (2005) and BOSCHMA and WAL (2006) all argue that the absorptive capacity of firms in a cluster affects the knowledge exchange among them and that the difference in the firms' absorptive capacity leads to a heterogeneous distribution of knowledge in the cluster. Although such micro-variable focused studies help deepen our understanding of the phenomenon of intra-cluster knowledge diffusion, so far not enough attention has been paid to a firm's knowledge structure, another important micro-variable. In our view, the efficiency of knowledge diffusion between firms may be dependent more on whether the knowledge fits into their knowledge structures than what type of knowledge is diffused (tacit or codified). To some extent, a cluster's cognitive community formed by the similarity of knowledge structures determines the efficiency of knowledge diffusion within it.

From the view of firms in a cluster, cognitive proximity may be the necessary condition for knowledge diffusion between firms in it, and a cluster's efficiency of knowledge diffusion may depend on its distribution of knowledge. Borrowing the concept of schema from social cognition, we start by explaining the meaning of the term "knowledge structure of a firm in a cluster", and then develop our cognitive community-based analytic framework.

The perspective of cognition stresses the impact of an agent's existing knowledge structure on his/her perceiving, interpreting, analyzing and remembering the information received (WALSH, 1995). One of the most important concepts of cognition used in the area of psychology, sociology and management is schema (BARTUNEK, 1984; GIOIA and POOLE, 1984; LORD and KERNAN, 1987; HARRIS, 1994; RENTSCH and KLIMOSKI, 2001; WOEHR and RENTSCH, 2003). Schema is a sort of cognitive knowledge structure, representing "knowledge about a concept or type of stimulus, including its attributes and relations among those attributes" (FISKE and TAYLOR, 1991, p.98). Social psychologists have identified numerous groups of schema, the main ones including: person schemas, self-schemas, role schemas and event schemas. Existing studies show that schemas enable us to efficiently code and categorise information, and influence what we pay attention to and what we ignore, and what we remember about a social situation.

The concept of schema from social cognition may be useful in interpreting the influence of firms' knowledge structures on the process of knowledge diffusion between them. In the view of cognition, the knowledge structure of a firm determines not only its absorptive capacity but also its information processing procedure, including perceiving, encoding, memorizing and inferring. As knowledge about any stimulus can be schematized, individuals have numerous schemas at their disposal (RUMELHART, 1984). According to this, HARRIS (1994) uses concepts such as organisation schema and object schema to investigate the impact of organizational culture upon individual sense-making. What kinds of schema are most relevant to understanding intra-cluster knowledge diffusion? Given that technological and business knowledge are the most exchanged in a cluster and are the most important factors for the development of firms, we propose that a firm's knowledge structure is comprised of two types of schema[1]: technological schema and business schema. These schemas capture the range of knowledge a firm uses to make sense of knowledge diffused in a cluster.

(1) *Technological schema*. Technological schema refers to a firm's knowledge

concerning the concepts and processes of a certain type of technology. It includes not only the knowledge about what the technology is but also the evaluation and opinion about the technology. For instance, television producers may have different technological schemas on the high-definition technology. Some may know much about the LCD technology and rate it more promising and others may know more about PDP technology and think it superior to LCD. Apart from the concept and opinion of a technology, technological schemas include technological scripts, which describe a firm's knowledge about expected event sequences and appropriate operation in using the technology.

(2) *Business schema*. Business schema refers to the knowledge of concept and process about management and marketing in a firm's daily operation. For a firm, business schemas may include knowledge about how to do international marketing, how to manage workshops, and how to keep good relations with employees.

Once schemas have been established, they influence a firm's information processing in two ways:

(1) *Schema-driven effect.* Schemas guide the search for, acquisition and processing of information, and subsequent behaviour in response to that information. As people are limited in their ability and capacity to process information, schemas offer simplified ways to code and categorise new information, without the need to start from a blank sheet every time (FISKE and TAYLOR, 1991; PENNINGTON, 2000).

(2) *Perseverance effect.* Schemas that have become established and developed

from a great deal of experience may be quite resistant to change with pressure to maintain the status quo (FISKE and TAYLOR, 1991). That is, previously formed beliefs tend to persist even in the face of contradictory evidence.

Firms with similar schemas belong to a cognitive community (or schematic community). The similarity of schema articulates that commonality among the firms' schemas will be characterized by incomplete overlap (WOEHR and RENTSCH, 2003) as they will not be identical. Therefore, schema similarity refers to the degree to which firms in a cluster have similar or compatible knowledge structures for organizing and understanding cluster-related phenomena. The schema similarity consists of two components: schema congruence and schema accuracy. Schema congruence exists when firms' schemas are compatible in content and/or structure. For example, if firms A and B's schemas of client services contain 'delivery in time', then their schemas of client services have some degree of congruence. Schema accuracy refers to the degree to which a firm's schema is similar to a 'true score' or target (RENTSCH and KLIMOSKI, 2001). For example, firm A's schema of firm B's adherence to customers' value is accurate when B actually believes that the adherence to customers' value is very important.

As schemas become more complex, they may develop into some sub-schemas. Firms in the same type of cognitive community will fall into different sub-cognitive communities by their development stages of schemas (see Fig. 1).

***Fig. 1. The Classification of Cognitive Community*[2]**

<Fig 1 about here>

The concept of cognitive community is more focused on the similarity of knowledge structure, and this is different from the concepts of community or community of practice often used by some researchers. A cognitive community is not an observable or real entity, and lacks a definite object or structure as a community and community of practice, so that even the members of a cognitive community may not be aware of their own membership.

As a firm's schemas influence its whole information processing procedure (including perceiving, encoding, memorizing and inferring), a cognitive community formed by schematic similarity has two important effects on intra-cluster knowledge diffusion:

(1) *Cognitive community's blocking effect on knowledge diffusion.* As soon as they have been established, schemas take place in a firm's information processing procedure. Firms with a similar (or the same) type of schema enjoy higher efficiency of knowledge diffusion than firms with different types of schema. Given the schema-driven effect, a firm is more sensitive to the information most relevant to its schema, and may ignore other information. The priming effect also shows that a schema activated recently is most likely to be reactivated (FISKE and TAYLOR 1991). As firms are limited in their ability to process information, and as the information received is often fragmentary and passing, without the help of schemas firms can hardly make sense of any information circulated in a cluster. Only firms with similar schemas can exchange knowledge through such fragmentary and passing information. COWAN et al. (2000) argue that, as some of the knowledge diffused is highly

complex, only a knowledge sender and receiver with the same codebook can communicate well with each other. The schema in our framework is equivalent to the codebook. With a similar schema, knowledge flows within channels of this specific cognitive community. In this sense, there is a blocking effect on knowledge diffusion between firms with different schemas.

(2) *Cognitive community's filtering effect on knowledge diffusion.* A filtering effect takes place between sub-cognitive communities within a general cognitive community at different development stages. As schemas become more complex, they may develop into some sub-schemas. Even for sub-schemas of the same type, their degrees of precision are different by their stages of development, which affects firms' information processing efficiency and speeds (FISKE and TAYLOR, 1991; COWAN et. al, 2000). Firms with less developed (or coarser) schemas sometimes may not understand the information diffused from firms with well-developed (or finer) schemas. It is equivalent to what happens in computer software development: an old edition of word processing software cannot be used to read or edit a file produced by a new edition, but the new version can be used to edit either version of the file. REED and DEFILLIPPI's (1990) study on imitation between firms in an industry also shows that the difference in the stage of knowledge development raises the barrier to imitation.

Obtaining the membership of a cognitive community by schema similarity, firms enjoy efficient knowledge diffusion. Given the blocking and filtering effects, intra-cluster knowledge diffusion behaves in a cognitive community-based style. In fact, because of the difference in firm knowledge structure, knowledge is not diffused evenly in a cluster. Fig. 2 presents an illustration of cognitive community-based intra-cluster knowledge diffusion.

Fig. 2. The Cognitive Community-based Intra-cluster Knowledge Diffusion

<Fig 2 about here>

In Fig. 2, firms A and B are assumed to be classified into different cognitive communities due to their schema similarity patterns. Firm A is a member of the technological cognitive community (T1-4)[3] and business cognitive community (B1-4), (B3-4), and firm B is a member of the technological cognitive community (T4-3) and business cognitive community (B1-1), (B3-4). As firms A and B belong to different types of technological community (T1-4) (T4-3), knowledge diffusion between them is not efficient due to a cognitive community's blocking effect. In other words, firm A can hardly learn the knowledge in the cognitive community (T4-3) from firm B, and vice versa.

What happens in the business cognitive communities represents both the blocking effect and filtering effect. As firms A and B belong to the business cognitive communities (B1-4)、 (B3-4) and (B1-1)、(B3-4) respectively, both are members of a cognitive community of the same type, and the only difference between them is their development stages of schema. Firm A in the business cognitive community B1 has a more developed schema than firm B, and firms A and B have schemas at a similar development stage in business cognitive community B3. The different business knowledge structures of firms A and B make knowledge diffusion between them asymmetric. Firm A may be more efficient than B in learning by a cognitive community's filtering effect in business cognitive community B1. However, in business cognitive community B3, both firms can diffuse knowledge with efficiency as they have schemas at a similar development stage. It needs to be noticed that the existence of a cognitive community's blocking effect may prevent the firms from enjoying high efficiency of technological knowledge diffusion in other business cognitive communities (such as B1) even though they are both the members of a highly developed cognitive community (B3).

To sum up, our cognitive community-based analytic framework for intra-cluster knowledge diffusion argues that the cognitive community formed through the cognitive proximity between firms is the fundamental way of knowledge diffusion in the cluster, so that only those firms who have a similar knowledge structure will be efficient in learning and transferring knowledge. In addition, on the cluster level, knowledge distribution of a cluster has a critical effect on knowledge diffusion within it. In a cluster with highly homogeneous firms' knowledge structures, knowledge diffusion would be active, as most firms belong to proximate cognitive communities. On the contrary, in a cluster with highly heterogeneous firms' knowledge structures, knowledge diffusion would be inactive and knowledge would flow in an uneven way, as most firms are located in the many scattered cognitive communities and knowledge transfer across communities is difficult.

3. CASE STUDY

Since the 1990s, a number of industrial clusters have emerged in China where thousands of firms in related industries have agglomerated. Among industrial clusters in China, the most remarkable ones are located in the Pearl and Yangtze River Deltas. The former Delta focuses on electronics, communication equipment and chemicals and the latter on textiles and home appliances. Industrial clusters in these two areas are highly competitive in both the home and overseas markets (ZHANG et al., 2004; ENGARDIO and DEXTER, 2004). Zhejiang Province is located in the southern part of the Yangtze River Delta, which covers a total land area of 101,800 square kilometers. There are 11 cities under the direct jurisdiction of the Zhejiang provincial government, including Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou and Lishui, under which there are 36 counties, 22 town-level cities and 30 county-level districts. As one of the most economically vibrant and developed provinces, Zhejiang ranks fourth in China in terms of overall economic output, and the economy is characteristic of hundreds of industrial clusters in various industries, such as textiles, garment, socks, ties, auto parts, plastics and mould. According to the Zhejiang Statistical Yearbook 2007, the economic output of these industrial clusters has made up approximately 50 per cent of the province’s GDP in 2006. As the Datang Sock Cluster (DSC) in Shaoxing City of Zhejiang Province is representative of traditional industrial clusters in China, the case study on it would provide some insights into the underlying causes of the competitiveness of China's traditional industrial clusters, and even for similar traditional clusters in other countries.

In this section, to further explore and verify the cognitive community-based analytic framework presented above, we report a case study of eight representative firms in the DSC. Table 1 summarises the major characteristics of the firms. The identities of these firms are disguised to ensure confidentiality.

Three factors were considered for the case selection. Firstly, cases were in industrial clusters with strong competitive capabilities. Secondly, firms were representative in size, from small to medium and large. Thirdly, for the data stability, only firms which had been in operation for at least three years would be chosen.

Although the sock production industry is less knowledge intensive than the electronics, telecommunication and biotechnology industries, a study of knowledge diffusion in this industry is still valuable. It is undeniable that low labour cost is an important element of competitiveness for traditional low-technology and low-knowledge intensive clusters. However, considering the fact that every region in China enjoys such advantage, it is hard to explain why most of the competitive clusters have only emerged in limited places such as the Pearl and Yangtze River Deltas and not evenly throughout the nation. Factors other than labour cost may have had an important effect on the success of such traditional clusters. In our view, competitive advantage of Chinese traditional clusters does not depend merely on low labour cost. Rather, knowledge may be crucial. PORTER (1998) argues that "there is no such thing as a low-tech industry. There are only low-tech companies". Although the sock industry is traditionally labour-intensive, there are extensive knowledge learning and diffusing activities, and business knowledge may be more important for a study of traditional industries. Actually, studies on traditional industries by BOSCHMA and WAL(2006), BELL and ALBU (2005) and GIULIANI (2005) have proved this.

The Datang Sock Cluster is in Datang, a small town in eastern Zhejiang Province. Sock production is the pillar industry of Datang. There are more than 10,000 sock makers in the town at present, with more than 200,000 employees. There are about 100,000 sock-knitting machines in Datang, including more than 40,000 top grade computer knitting machines and 20,000 associated facilities. DSC holds a very important position both in the Chinese and global sock-making industry (ZHANG et al., 2004; LEE, 2005; DATANG TOWN GOVERNMENT, 2005). According to the statistics from Macrochina Database published by the Chinese National Bureau of Statistics, China produced about 18 billion pairs of socks, among which Datang produced 12 billion pairs, accounting for 67 per cent of total domestic and 35 per cent of global output in 2004.

Sock-making in Datang can trace its history back to the 1930s, when a few craftsmen produced socks with manual sock machines in their homes to meet local needs. The development of the modern sock industry in Datang has gone through three stages. Between the 1970s and the mid-1980s, with the transition of the planned economy, some town- and village-owned sock factories were established, including

Chaota, Zhongjia, Anhua and Chenshan Sock Factory. From the mid-1980s to the mid-1990s, with the deepening of economic reforms in China, most township and village-owned sock factories gradually went bankrupt and privatized, and many former workers began to run their own household sock-making factories on a small scale. From the mid-1990s to present, there have emerged many firms with large scale production among these household factories. Currently, sock firms in Datang can be classified into two types in terms of size: large (and medium) enterprises and small manufacturers. Large enterprises usually have the capability of large scale production, but they don't invest in the whole production process of sock-making. They are mainly concerned with obtaining big orders from foreign buyers such as Wal-Mart or Carrefour. After getting these orders, they subcontract to small manufacturers who produce semi-finished socks for them, and then accomplish the final stage of production such as packing. On average, a large enterprise will have about 20 to 30 small manufacturers to fulfill orders, and a small manufacturer would have to act as a supplier for one or more large/medium enterprises. Small manufacturers account for approximately 90 per cent of the total number of sock firms in Datang.

3.1 Data Collection and Codification

3.1.1 Data Collection

We conducted in-depth interviews with the general or deputy general managers and chief engineers of the eight firms listed in table 1. Each interview lasted for about one and a half hours on average. Interviews were tape-recorded unless the informants objected. To assure the accuracy of the interview data, we conducted member checks

(YIN, 1981; YAN and GARY, 1994). All the interviews were conducted during October and November 2006. In addition to interviews, approximately 30 pages of archival data were collected for each firm, including the information about the firm's history, strategies, and main clients.

Table 1. Summary of the Major Characteristics of the Firms [4]

<Table 1 about here>

3.1.2 Data Coding

Data from the interviews and archives were coded using content analysis methods. Firstly, we coded all data into a number of categories according to the proposed theoretical framework. These categories are (1) type of technology, (2) level of technology, (3) technological development strategy, (4) market orientation, (5) market development ability, (6) business strategy, (7) channels for acquiring technological knowledge, and (8) channels for acquiring business knowledge.

Secondly, we created subcategories according to the characteristics of the above categories. For example, three subcategories: international market, home market, and local market, were grouped into "market orientation". Table 2 shows an example of data coding for one of the eight firms.

Table 2. Examples of Data Coding [5]

<Table 2 about here>

Data coding was completed by three team members participating in the interviews. We jointly developed the coding category in the first stage and used it to code one case. Then, the three team members each specialised in coding, auditing and checking for the remaining seven cases. The auditing and checking consisted of two steps: the confirmation and double checking of data coding.

3.2 Results

Our study on the DSC shows that knowledge distribution of a cluster has a significant influence on knowledge diffusion within it. Firms in DSC have a high degree of homogeneity in technological knowledge, and are located within a proximate cognitive community. In conformity with our cognitive community-based analytic framework, the knowledge diffusion between firms is very active and knowledge flows mainly in the local area. Contrary to the case of technological knowledge, firms in DSC have a high degree of heterogeneity in business knowledge so that it is hard for knowledge diffusion between firms to take place intentionally or non-intentionally, so that knowledge flows suffer from stickiness.

DSC also shows that the combination of similarity in technological knowledge and divergence in business knowledge facilitates local flexible production and contributes to the competitiveness of the cluster. For technological knowledge, homogeneity guarantees that a sufficient number of local firms will participate in the related sectors and fulfill re-allocated orders. For business knowledge, heterogeneity ensures that only a few firms have the ability to integrate local flexible production to achieve economies of scale and efficiency.

3.2.1 Knowledge Distribution of Firms in DSC

From the case studies it can be seen that the knowledge structures of firms in DSC were neither purely heterogeneous nor completely homogeneous, because the distribution of technological and business knowledge exhibited different patterns. Fig. 3 indicates that the sample firms are highly similar in the technology but significantly different in the business dimension.

***Fig. 3 The Distribution of Knowledge Structure in DSC*[6]**

<Fig 3 about here>

The firms have no fundamental differences in both the technological selection (traditional sock-producing technology) and current technological levels. From a cognitive community perspective, firms in DSC are in the proximate cognitive community of technological knowledge. Three factors may explain this result. Firstly, the technologies and methods the firms adopted are comparatively traditional. Although the machines are imported from Italy or Japan, the operational principles are basically the same. Secondly, computerised sock knitting machines have gained prevalence in this area since year 2001, and most machines firms purchased were similar. Technological problems and solutions are also basically the same. A third and probably the most important factor is that the collective enterprises (or township-and-village enterprises, TVEs) established at the very early stage promoted the technological knowledge similarity between firms in DSC. Most entrepreneurs and technicians in DSC originated from several TVEs in the 1980s, and have acted as technological knowledge disseminators, leading to a reasonably homogeneous distribution of technological knowledge in DSC.

We failed to detect a positive relationship between the technological level and firm size. For example, case JC is very small in size, but its technological level is comparable to those of large enterprises. One deputy general manager of the large firm WY gave the following comments on small firms specializing in outsourcing during his interview:

These producers are relatively strong in technology. Sometimes we even consult them when we have problems in our internal production. After all, they have been producing socks for ten to twenty years, and are very experienced. They are good at technology, but there exists a very large gap between them and us in other aspects, particularly in management and operational thoughts, and it's hard for them to develop. At present, nearly 30% of the firms in Datang are our suppliers, and some have been doing this for eight or ten years. *-WY D. GM*

Different from their high congruence on technological knowledge structures, firms in DSC have great diversity in business knowledge, especially between large/medium-sized enterprises and small manufacturers[7]. In other words, from the perspective of business knowledge structure, there are several sub-cognitive communities at different development stages in DSC. Large/medium-sized enterprises are at higher stages than small manufacturers in production management knowledge. In terms of operational knowledge in international marketing, the difference is even greater. Small manufacturers have so little knowledge about international marketing that they know little about and never bother to know about the international market. In terms of brand management knowledge, medium-sized enterprises are significantly different from large ones.

The export ratio of large/medium-sized enterprises in DSC is about 70%, and these firms normally take international marketing seriously and pay close attention to the accumulation of international marketing knowledge. They are conscious about the development trends of the industry. The deputy general manager of BP pointed out the following during the interview:

We must be concerned about international trade policy, e.g. antidumping and quota, because they have great impact on our operation and production. The year before last, the US government imposed quota limits on Chinese socks, which brought great pressure on us. We did all the following to tide over the crisis: quickening the pace to develop other external markets such as Japan, Korea and Europe, increasing added value of products to raise profit margins, establishing overseas entities to avoid tariff barriers, improving the competitiveness of the firm, and obtaining accreditation of product quality (ISO9000 and ISO14000) and environmental protection (green textiles). . *–BP D. GM*

Two small-sized firms, JA and JB, are typically representative of small manufacturers in DSC. These producers usually had fewer than 20 employees, and specialised in supplying large or medium-sized firms. They had neither proper management systems nor marketing staff and the entrepreneurs did all the managerial work. Their communication circles were largely restricted in DSC. Though good at sock-producing technology, these firms were not so at management and marketing. The boss of a small-sized firm talked about the influence of industrial development on his business:

We usually don't care about where these products are exported. We just take orders from and make socks for large-sized firms. Sometimes they turn to us for technological advice, and they are inferior to us in technology. However, we don't do such things as customs declaration, inspection, document attachment or management. We just employ several people to produce socks.

–JB Boss

As mentioned earlier, there are huge gaps in business knowledge structures between the large and medium-sized enterprises, especially in brand management. The large and medium-sized sample firms are engaged in both domestic and export sales, but only three firms have their own brands, and two of the brands are influential on the domestic market. In most circumstances, AL uses its own brand for export sales. Other medium-sized firms mainly do outsourcing for other brands and know little about brand management and operating modes.

To sum up, the two dimensions of knowledge distribution of DSC diverge. In terms of technological knowledge, a high degree of homogeneity can be found and there is no significant difference in the level of technological knowledge between firms of different size. In contrast, when it comes to business knowledge, a high degree of heterogeneity can be identified and a firm's level and type of business knowledge are significantly related to its size. On the basis of the information collected from interviews, we reckon that the similarity of technological knowledge and heterogeneity of knowledge between firms in DSC may result from some unique characteristics of TVEs.

TVEs were distinct products of China's transitional economy. It is very different from the western system under which the individual is the ultimate owner of property (BOWLES and DONG, 1999). It is a unique form of enterprise organisation based on collective ownership and its property rights are in practice exercised by Town and Village Governments (TVGs) (NAUGHTON, 1994). TVGs who own and control TVEs have an objective defined more broadly than narrow economic interests and profits. It may include social as well as ideological interests. In particular, it usually includes employment maximisation. TVGs place a strong priority on employment generation. Accordingly, most employees in TVEs come from local towns or villages (BOWLES and DONG, 1999). In the context of DSC, small manufacturers appeared in the mid-1980s and entrepreneurs of large enterprises emerged in the 1990s. Almost all of them have had work experiences in TVEs and many entrepreneurs started their business through privatization of the bankrupt TVEs. In the 1970s and early 1980s, China was still a relatively isolated planned economy and TVEs focused their efforts mainly on manufacturing and local trading rather than modern business activity such as brand management, marketing planning and international trading. TVEs were more willing to transfer knowledge and provide skill training than private owned or state owned enterprises, making it easy for local employees to acquire technological knowledge from them. However, as TVEs themselves were not good at modern business management, they were unable to diffuse business knowledge effectively in the region.

This historical factor has led to high heterogeneity of business knowledge and high similarity of technological knowledge in DSC. At present, most sock firms in DSC are small manufacturers who focus mainly on manufacturing semi-finished socks. Only a few firms have learnt new business knowledge outside the cluster since the privatisation of TVEs, and have the ability to incorporate small firms into their subcontracting networks in DSC. Consequently, those with good business knowledge have developed faster than others and grown into large enterprises.

3.2.2 Knowledge Diffusion Patterns in DSC

As described before, firms in DSC participated in different cognitive communities according to their knowledge structures. The case study indicates that a cognitive community's blocking and filtering effects have an important impact on knowledge diffusion between firms in DSC.

In DSC, all firms selected almost the same technology, reached similar technological levels, and were highly congruent in the technological knowledge structure. In fact, they were in the same technological cognitive community. During the interviews, we found that the firms frequently communicated with each other on technological affairs, and this is similar to Marshall's "industrial atmosphere". Fig. 4

shows that localised technological knowledge is transmitted with extraordinarily high efficiency and speed because the firms have a similar technological knowledge structure.

Fig. 4 Main Channels for Acquiring Technological Knowledge[8]

<Fig 4 about here>

It is noted that technological knowledge diffusion was not intentional by the firms. In fact, the firms took various measures to keep their knowledge a secret, but spontaneous knowledge spillover was unpreventable because the firms had similar technological knowledge structures. The deputy general manager of WY and the chief engineer of AL said:

We usually sign agreements on secret information with subcontractors … but the effects are limited, and there'll be a lot of similar socks in Datang in several months… We have no choice but to accelerate the pace of releasing new products!

-WY V.CEO

Generally speaking, because we have been making socks for so many years, we could tell how to produce new products or new styles on the market simply by glancing or touching them. *-AL CTO*

We also notice that the frequent interaction between the small manufacturers and large enterprises involved only technological knowledge, rather than knowledge in international trade and brand management. On the contrary, while there are no close business relations, the medium-sized enterprises claimed that they obtained much important information from the large enterprises in the cluster.

Sometimes we help small makers in production management to control product quality, but they are slow learners, and we have to fill some important orders on our own. Our experience in management and international trade is our competitive edge, and they lag behind a lot (on these aspects) even after seven or eight years of cooperation. *- WY V.CEO*

They taught us useful knowledge about production and workshop management, and we love to learn. But we do not know how to learn international trade. We just fill the order, that's OK. *–JC BOSS*

In fact, these phenomena reflected the blocking effect of a cognitive community on knowledge flows. Even though geographical and relational proximity exist between small and large manufacturers, and even though they have long term cooperation, it is very hard for the small manufacturers to learn (international trade knowledge) because they are not in the same cognitive community of business knowledge. The medium-size enterprises have no close business links with the large ones, but they are in the same cognitive community, and could be enlightened upon some phenomena seeming irrelevant. As indicated in Fig 5, the most important channel for firms in DSC to gain business knowledge is self-study.

Fig.5 Main Channels for Acquiring Business Knowledge[9]

<Fig 5 about here>

The knowledge distribution between firms in DSC was homogeneous in technology and heterogeneous in business knowledge. Technological knowledge diffused under the control of a cognitive community's filtering effect, i.e. technological learning mainly centered in DSC. On the other hand, a cognitive community's blocking effect is evident in business knowledge diffusion, i.e. firms in different business schema communities are significantly different in their learning efficiency. The results suggest that firms' knowledge structures have a significant impact on knowledge diffusion in DSC, and the existence of the blocking and filtering effects in cognitive communities directly shape the mechanisms and efficiency of knowledge diffusion.

In addition, our findings suggest that the complementarity between business knowledge heterogeneity and technological knowledge congruence is an important factor that has led to competitive advantage of DSC. A powerful flexible production system has been developed in DSC because of high homogeneity in technological knowledge, and large enterprises have been brought up with business knowledge heterogeneity.

In fact, large enterprises play the role of leadership in DSC. They hold relatively abundant managerial knowledge, have a better understanding of foreign buyers' needs, and are more experienced in production management and quality control. After getting big orders from overseas, they divide and subcontract them to dozens of small manufacturers. In this way, they realise a flexible production with low cost. From the perspective of the cognitive community, this kind of production can be realised because of the existence of high-level but low-heterogeneity sock producing knowledge in DSC. Therefore, the case study not only further verifies the explanatory power of the cognitive community-based analytic framework for intra-cluster knowledge diffusion, but also leads us to an important discovery that the combination of various dimensions of knowledge distribution may be a new approach to explain the formation and development of a cluster. That is to say, it seems that a cluster's competitiveness is derived from a flexible production system within it, but a more fundamental factor is the combination of various dimensions of knowledge (e.g. technological and business knowledge) among the firms within it.

4. SIMULATION STUDY

The case study provides a snapshot of intra-cluster knowledge diffusion in DSC. Since firms in Datang reached a high level of similarity in technological knowledge, they have achieved diffusion efficiency in technology by the filtering effect of a cognitive community. In contrast, due to their high dissimilarity in business knowledge, the diffusion efficiency is low by the filtering and blocking effects of a cognitive community. Even between those firms who have similar technological knowledge and have developed a long term partnership, the diffusion of business knowledge is still very hard due to the existence of the cognitive community's blocking effect. Consequently, our case study shows that a cluster's distribution of knowledge through the filtering and blocking effects of a cognitive community does determine the process of knowledge diffusion in the cluster. However the case study only provides a static cross-sectional description of knowledge diffusion in the cluster. There is a dynamic relationship between knowledge distribution and knowledge diffusion as they affect each other. The case study does not tell us this dynamic process. For example, it is uncertain what will happen to knowledge diffusion when both the heterogeneity and level of knowledge distribution are taken into consideration, and whether a higher level of knowledge distribution leads to more effective knowledge diffusion. Moreover, although it verifies the cognitive community-based analytic framework for intra-cluster knowledge diffusion, the case study is concerned with a traditional industrial cluster in China only. It is very difficult to control proximity factors, e.g. industry and regulation, and to conclude whether the knowledge diffusion pattern in DSC is a special case only.

To compensate for the deficiencies of the case study, we use an agent-based simulation to simulate the dynamics of knowledge diffusion in a cluster, aiming to find out whether the blocking and filtering effects of a cognitive community take place in the short or long term, and obtain a better understanding of the phenomenon of knowledge diffusion in a cluster.

Agent-based simulation is now recognised as one of the most promising new tools for regional study, allowing us “to understand better the relations between micro-processes (the decisions and behaviors of economic actors) and the emergence of stylised facts common across much of industry (relating to R&D and the geography of firms) in the model output” (TAYLOR and MORONE, 2005). Recently GILBERT et al. (2001), PAJARES et al. (2003), MORONE and TAYLOR (2004) and COWAN and JONARD (2004) have all used the agent-based methodology to study innovation dynamics in clusters.

4.1 A Cognitive Community-based Knowledge Diffusion Model

We assume a global environment G consisting of a grid of $W \times W$ cells and a population of N agents (N < $W \times W$), representing a cluster and firms in it respectively. The grid is wrapped (i.e. a torus) so that there are no edge effects. Each agent is initially assigned a random position in the grid. Not all the cells of the grid are occupied by agents, and those occupied are occupied by only one agent. To simulate knowledge diffusion in the cluster, every agent $i \in \{1, 2, ...N\}$ is endowed with two types of knowledge randomly: the initial level of technological knowledge $k_i^T \sim U[T_d, T_u]$ and the initial level of business knowledge $k_i^B \sim U[B_d, B_u]$.

Given these types of knowledge in the cluster, every agent i has two sets of acquaintances: $\Gamma_T(i,t)$ and $\Gamma_B(i,t)$, representing the agent's technological and business acquaintances at cycle t. Agent i's initial technological acquaintances $\Gamma_T(i,0)$ and business acquaintances $\Gamma_B(i,0)$ are all other agents on its MOORE neighborhood: those cells adjacent in the eight directions (north, south, east, west, northeast, northwest, southeast and southwest) and within the agent's visible range[10]. In our model, we call the unit of time a 'cycle'. In each cycle, every agent is permitted to interact with two acquaintances randomly chosen: technological acquaintance $p \in \Gamma_T(i,t)$ and business acquaintance $q \in \Gamma_B(i,t)$. Why does the agent choose two acquaintances respectively? The answer is that, according to the blocking effect of cognitive community, knowledge transfer may be more effective between firms belonging to the same type of cognitive community.

After agent i 's interacting learning with the acquaintance p and q, it will randomly choose another two agents $k \in \Gamma_T(p,t), l \in \Gamma_B(q,t)$ from the acquaintance set of the two acquaintances interacted with and add the two new acquaintances to agent i 's sets of acquaintances $\Gamma_T(i,t+1), \Gamma_B(i,t+1)$ respectively. Consequently, with the simulation process, agent i 's two sets of acquaintances will become larger and larger.

We suppose that while the interaction between agents i and j takes place, only the agent who launched the interaction will have gains from interactive learning. Agent i 's gains from the interaction are calculated in the following steps (MORONE and TAYLOR, 2004):

Firstly, we calculate the distance in two types of knowledge between agents i and j :

$$\delta_i^T = k_j^T - k_i^T \ , \ \delta_i^B = k_j^B - k_i^B$$

Then we calculate the knowledge/distance ratio in technological and business dimensions:

$$\varphi_i^T = \frac{k_i^T}{\delta_i^T} \ , \ \varphi_i^B = \frac{k_i^B}{\delta_i^B}$$

Finally, we calculate agent i 's knowledge gains in two dimensions:

$$g_i^T = \max\{\min\{\varphi_i^T, \delta_i^T\}, 0\}, g_i^B = \max\{\min\{\varphi_i^B, \delta_i^B\}, 0\}$$

The above knowledge gain function embodies the filtering effect of a cognitive community: even for firms within the same type of cognitive community, knowledge diffusion between them still does not occur easily if the difference between their development stages of knowledge is too large. In Fig. 6, we depict agent i 's (where i

has different levels of knowledge: 1, 5, 10) knowledge gains that arise through interaction with agent j. We can see two things: the higher the level of the agent, the more it gains from interaction; and the smaller the difference between the two agents, the more the agent can gain.

To measure knowledge diffusion using a simulation, we provide two groups of indices: the average knowledge level $\mu^T(t)$, $\mu^B(t)$ and the standard variance of the knowledge level $\delta^T(t)$, $\delta^B(t)$. Using these indices and relevant figures, we can grasp some important information about knowledge distribution and diffusion in the simulation.

$$\mu^T(t) = \frac{1}{N}\sum_{i=1}^{N} k_i^T \quad , \quad \mu^B(t) = \frac{1}{N}\sum_{i=1}^{N} k_i^B$$

$$\delta^T(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \; k_i^T - \mu^T(t) \;^{2}} \quad , \quad \delta^B(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \; k_i^B - \mu^B(t) \;^{2}}$$

Fig. 6. The Knowledge Gain of Agent i with an Initial Level of Knowledge Equal to 1, 5 and 10

<Fig 6 about here>

4.2 Setting and Results of Simulation Experiment

4.2.1 Setting of Simulation Experiment

We performed the simulation with a population of 300 agents allocated randomly over a wrapped grid of dimensions 21×21 units (i.e. a total of 401 cells) (see Fig. 7). To explore the relationship between knowledge distribution and diffusion, the agent's initial interval of knowledge distribution is classified into three types: $[0,150][0,50][50,100]$, indicating high level and high heterogeneity of knowledge distribution (HH), low level and low heterogeneity of knowledge distribution (LL), and high level and low heterogeneity of knowledge distribution (HL)[11] respectively. Since there are two dimensions of knowledge, technological and business, combining the three types of knowledge distribution in each dimension, we will have nine (3×3) classes of cluster. As set in the simulation model, there is no difference in the agent's learning strategy in technological and business knowledge dimensions, and the diffusion of these two types of knowledge is operated independently by a cognitive community's blocking effect. To save space, in the next two sub-sections we mainly focus on the dynamics of technological knowledge distribution and diffusion, and the dynamics of business can be inferred from it[12].

Fig. 7. 300 Agents on the Wrapped Grids

<Fig 7 about here>

In the following part, we report the result of three clusters: high level and high heterogeneity of technological knowledge (HH), low level and low heterogeneity of technological knowledge (LL), and high level and low heterogeneity of technological knowledge (HL). Meanwhile, we let agents interact 30 cycles and 300 cycles to observe dynamics in both the short and long term.

4.2.2 Results of Long Term Analysis

After letting agents interact for a period of 300 cycles, we observed that irrespective of the initial distribution of technological knowledge, all three types of cluster almost converged[13]. The only difference between them is the velocity of convergence. The HL cluster converged first, followed by the LL cluster, and finally the HH cluster.

Fig. 8. The Long Term Dynamics of HH Cluster

Fig. 9. The Long Term Dynamics ofHL Cluster

Fig. 10. The Long Term Dynamics of LL Cluster

<Figs 8-10 about here>

Industrial technology progresses fast in a knowledge economy. The only way for firms to maintain competitiveness is to keep learning new knowledge of technology and business. Knowledge in a cluster converges in the long term so that it is very important for firms to acquire new knowledge rapidly and efficiently in the short term. We now analyse the short term dynamics of knowledge distribution and diffusion.

4.2.3 Results of Short Term Analysis

Knowledge diffusion dynamics in a cluster is comparable to macroeconomic evolution, and the short-term dynamics of knowledge diffusion may be more important for firms. Our results of the short term simulation show that in the HH, HL and LL clusters, the initial distribution of technological knowledge plays an important role in the dynamics of knowledge diffusion.

Fig. 11. The Short Term Dynamics of HH Cluster

Fig. 12. The Short Term Dynamics of HL Cluster

<Figs 11-12 about here>

In the HL cluster, the agents' technological knowledge quickly achieved convergence with a high mean and low standard variance. This may indicate that knowledge is diffused effectively between the agents by the filtering effect of a cognitive community when they all belong to a highly developed sub-cognitive community of the same type. Such high efficiency of knowledge diffusion is also evident in the graph of the agents' knowledge distribution at different stages. As the agents in the HL cluster have a comparatively high level of technological knowledge, after 20 cycles of simulation, almost all agents have achieved the level of knowledge 100, and all agents in the cluster have reached the level of knowledge 50 by cycle 30.

Fig. 13. The Dynamics of Agents' Distribution of Knowledge in the HL Cluster

<Fig 13 about here>

The filtering effect of a cognitive community is also evident in the LL cluster. Although the agents in the LL cluster have improved their technological knowledge through 30 cycles of interaction, the standard variance of the agents' technological knowledge has not declined, indicating that some agents have absorbed the knowledge very quickly but others have done it slowly. As the agents in the LL cluster have a relatively low level of technological knowledge, knowledge exchange among them is more difficult due to the filtering effect of the cognitive community. Some agents with a relatively high level of technological knowledge benefit a lot from the interaction, but other agents with a relatively low level of knowledge only benefit a little. From the graphs of the agents' knowledge distribution at different stages it can be seen that, after 20 cycles of simulation only half of the agents arrived at the level of knowledge 50, and even by cycle 30, some agents still had not reached the level of knowledge 50.

Fig. 14. The short term dynamics of LL cluster

Fig. 15. The Dynamics of Agents' Distribution of Knowledge in the LL Cluster

<Figs 14 and 15 about here>

The most interesting discovery of the short term simulation is the result of the HH cluster. From fig. 11, we can see that although HH has a relatively high level of average knowledge, its heterogeneous knowledge distribution leads to an extraordinarily low diffusion efficiency. This phenomenon is very interesting, because we usually expect that a high level of average knowledge distribution ensures active knowledge diffusion in a region. In reality, some regions replicate the development modes of other successful regions, and during the process, they focus particularly on the development of local research institutes to improve the average level of local knowledge distribution. However, this strategy does not often lead to an ideal result. The simulation in the HH cluster indicates that, although a high level of average knowledge distribution is of vital importance, distribution heterogeneity also plays a key role. To realise highly efficient knowledge diffusion in a cluster, we must ensure a high level and low heterogeneity of knowledge distribution among agents in the cluster.

The HL cluster represents a cognitive community with highly developed technological knowledge, and the LL cluster a less developed one, but the HH cluster represents one with significant differences inside. The simulation experiment on the three clusters shows that the filtering effect of a cognitive community is evident. Technological knowledge is diffused more effectively in HL than the other clusters. Firms in the HL cluster can learn more and at a higher speed.

In sum, the simulation of knowledge distribution and diffusion leads to two findings:

(1) In the long term, a cluster's initial distribution of knowledge has no significant effect on knowledge diffusion within the cluster. Irrespective of the initial distribution of knowledge, all agents in the three clusters can converge to the similar level of knowledge.

(2) In the short term, a cluster's initial distribution of knowledge has a critical effect on the process of knowledge diffusion. The HL cluster can stimulate knowledge diffusion among agents within it, enabling the agents to converge to a high level of technological knowledge more quickly than the LL cluster and HH cluster. Since the agents have a low initial level of technological knowledge, interactive learning between agents in the LL cluster is less effective. Most interestingly, although the HH

cluster has a high level of average knowledge, the differences between the agents are too dramatic, and the knowledge diffusion efficiency of the HH cluster is even lower than that of LL cluster under the influence of the filtering effect of the cognitive community.

Compared to the static results of the case study in section 3, our agent-based simulation reveals some interesting findings. As all agents in a cluster can keep learning for a long time to achieve a similar level of knowledge, the heterogeneity of technological knowledge in the cluster may be a short term phenomenon. However, the speed of the convergence process depends on the cluster's initial distribution of knowledge. A cluster with a high level but low heterogeneity of initial knowledge has an advantage in the speed of knowledge learning and diffusion. As shown in the short term simulation of clusters HL, LL and HH, both heterogeneity and the level of knowledge distribution play an important role in knowledge diffusion.

5. CONCLUSIONS

This paper has adopted a perspective of firm knowledge structure in a cluster to discuss the issue of intra-cluster knowledge diffusion. A cognitive community-based analytic framework is established, a case study on a cluster from China is conducted and an agent-based simulation is performed to further verify it. Several conclusions can be drawn from the case study and simulation:

1. Our cognitive community-based framework provides some new thoughts and insights into the phenomenon of intra-cluster knowledge diffusion. Given the

cognitive community's blocking and filtering effects, it is important to establish a high level and low heterogeneity of knowledge distribution in a cluster with which it will be relatively easy for knowledge to diffuse at a high speed. Our simulation study proves that knowledge diffusion in a cluster with a high knowledge level but low knowledge heterogeneity is most efficient, followed by the one with a low knowledge level and low knowledge heterogeneity, and finally by one with high knowledge level and high knowledge heterogeneity.

2. A cluster's knowledge distribution may not be as homogenous as the traditional wisdom would suggest. However, it may not be purely heterogeneous either. Our case study shows that knowledge distribution in DSC is relatively homogenous for technological knowledge but heterogeneous for business knowledge, which renders the cluster different diffusion efficiency in different dimensions of knowledge and gives DSC potential for success. Given the homogeneous distribution of technological knowledge, firms in DSC belong to the same cognitive community at a high development stage, leading to fluent and efficient local learning and diffusion of technological knowledge. This pattern of technological knowledge diffusion is very much like the "industrial atmosphere" described by Marshall. In contrast, as DSC has a heterogeneous distribution of business knowledge, the diffusion of such knowledge is rare. Even for firms maintaining technological cooperation for many years, there is little business knowledge diffusion. Apart from several large firms acquiring business knowledge from outside DSC, most small and medium-sized firms learn business knowledge by self study. While existent studies either presume knowledge

homogeneity or merely consider technological knowledge and neglect the business dimension, our investigation considers multi-facet knowledge distribution and hence provides new insight into the phenomenon of intra-cluster knowledge diffusion.

3. In a cluster, some firms may hold the position of “gatekeepers” by their knowledge endowments, and they may determine the characteristics and development direction of the cluster. In DSC, the leader firms behave differently in the technological and business cognitive communities. In the technological cognitive community, they have to act as “generous gatekeepers” to communicate with others either consciously or unconsciously, because firms in DSC have highly homogeneous technological knowledge, and because it is very difficult to keep technological knowledge secret due to the filtering effect of a cognitive community. However, the leader firms in DSC behave more like “stingy gatekeepers” in diffusing business knowledge. These leader firms may exploit business knowledge exclusively by the cognitive community’s blocking and filtering effect, as firms are highly heterogeneous in business knowledge,

4. Both the case study and simulation indicate that a high knowledge level but low knowledge heterogeneity in a cluster can have a very important impact on its competitiveness. However, due to the lack of a public knowledge infrastructure basis, such as resources in science and technology education and social service organisations, it is hard for most developing countries to obtain the important initial distribution of high-level knowledge with low-knowledge heterogeneity in order to realise large-scale diffusion of knowledge and skills in the short term. Nevertheless,

we have found that collective enterprises or town-and-village enterprises, a product of China's transitional economy, laid an important foundation for the formation of high-level knowledge and low-knowledge heterogeneity in DSC in the 1980s. Although most collective enterprises or town-and-village enterprises went bankrupt or were privatised in the 1990s, the initial knowledge distribution they formed was an important premise for the development of DSC. It shows that for clusters in developing countries, even developed ones, an appropriate knowledge distribution is the prerequisite condition for their formation and development. From the experiences of China's clusters such as DSC, TVEs as a product of transitional economy contributed much to building such knowledge distribution. Even though other countries may not have such historical opportunities, there are many equivalents such as universities or trade unions which can have similar effects.

5. Last but not the least, our research provides a new explanation for sources of a cluster's competitiveness. Our case study shows that the combination of various dimensions of knowledge distribution may be fundamental for the formation and development of a cluster. That is to say, it seems that although a cluster's competitiveness is derived from the flexible production system in it, a more fundamental factor is the combination of various dimensions of knowledge (e.g. technological and business knowledge) among the firms in it. In DSC, there is a high-level homogeneity distribution of sock producing knowledge and high heterogeneity distribution of business knowledge, which gives large enterprises an opportunity to utilise the local capacity of low cost flexible production. By their

relatively abundant managerial knowledge, better understanding of foreign buyers' needs, and greater experience in production management and quality control, large enterprises often get big orders from overseas. As there are numerous small manufacturers with high sock producing technology, large enterprises divide and subcontract foreign orders to these partners conveniently. In this way, they realise flexible production with low cost and gain tremendous advantage over their competitors located outside DSC.

The study is an exploratory one using a perspective of the cognitive community to interpret the phenomenon of intra-cluster knowledge diffusion. Several limitations need to be noticed and overcome in future.

(1) Our analytic framework is focused on intra-, rather than extra-cluster knowledge diffusion, and the knowledge transferred from outside is not discussed in detail. Kowledge diffusion from outside may be very important for a cluster's development and innovation. As BELL and ALBU(1999) point out, for developing countries, the need for technological chasing and developing means that extra-cluster knowledge diffusion may have a great impact on cluster development. In future, a study incorporating outside knowledge diffusion into the analysis would enable us to know more about the topic.

(2) Our cognition-based analytic framework argues that only those firms with similar knowledge structures would be efficient in learning and transferring knowledge. This framework is in nature a knowledge diffusion model, implying that a small knowledge gap between firms facilitates knowledge learning and diffusion. Although

the diffusion of similar knowledge enhances firms' technological capabilities and places them in a better position for innovation, our paper has not provided an explicit discussion of the relationship between knowledge diffusion and innovation while advancement in a cluster demands further knowledge that allows modernisation, innovation and adjustment. Consequently, in future research more attention should be paid to the relationship between innovation and diffusion.

(3) In addition to firm knowledge structures, other micro-level variables such as strategy orientation, organisational structure and entrepreneurship need to be considered in future studies of cluster knowledge diffusion.

(4) Although DSC is representative of China's traditional clusters, our case study covers 8 firms only, which may limit the interpretation of the findings from this study. A larger sample size would be preferable in future research.

(5) In order to simplify the simulation model, we do not distinguish between large and small enterprises and we assume that all firms have complete information about each other's knowledge, which may restrict the model's explanatory power.

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NOTES

1. SHANE (2000) proposes that three dimensions of prior knowledge are important to the process of entrepreneurial opportunity discovery: prior knowledge of markets, of ways to service markets, and of consumer problems. TSAI (2001) and COHEN and LEVITHAL (1990) suggest that technological knowledge is an determinant of a firm's competitiveness. In addition, NOOTEBOOM et al (2007) define a firm's knowledge base as its technological knowledge. Furthermore, in the tradition of research in managerial and organizational cognition (WALSH, 1995), schema and knowledge structure are used interchangeably.
2. In Fig. 1, CC1 represents a cognitive community of type 1, so do CC2, CC3,….
3. We represent a cognitive community in the following way: the first letter denotes the category of knowledge, technological or business; the first and second numbers indicate the type and development stage of a schema respectively. The greater the second number the more developed a schema. For example, (B3-1) represents a less developed business schema of type 3.
4. According to the characteristics of the Chinese sock industry, we define firm size as: small, staff number≤100; medium, 100 < staff number≤300; large, staff number > 300.
5. Because of space limitations, we list the classification of the first level categories only.
6. For the convenience of diagram drawing, we use different symbols to represent different firm sizes. A star represents large size; a diamond represents medium

size; and a triangle represents small size. In the diagram, the ordinate stands for knowledge type, and the abscissa for the development level of certain knowledge type.

7. As there is a significant relationship between the level of business knowledge and firm size, we reckon that business knowledge may be more important for a firm's competitiveness.
8. The assessment indexes are formed according to the relevant information about channels for obtaining technological knowledge in the coding part. All important channels mentioned by the interviewees are listed.
9. The assessment indexes are formed according to the relevant information about channels for obtaining business knowledge in the coding part. All important channels mentioned by the interviewees are listed.
10. In the model, we set an agent's visible range to 1.
11. Here, we set the probability distribution of the agent's knowledge as uniform distribution,

    $X \sim U(0,150), E(X) = 75, D(X) = 1875$ $Y \sim U(0,50), E(Y) = 25, D(Y) = 208\frac{1}{3}$;

    $Z \sim U(50,100), E(Z) = 75, D(Z) = 208\frac{1}{3}$
12. The detailed simulation results of other classes of cluster are not presented because of space limitation but available upon request.
13. This seems to confirm a common saying that "time permitting, we can do anything". So long as agents continue learning, they will eventually achieve their objectives.

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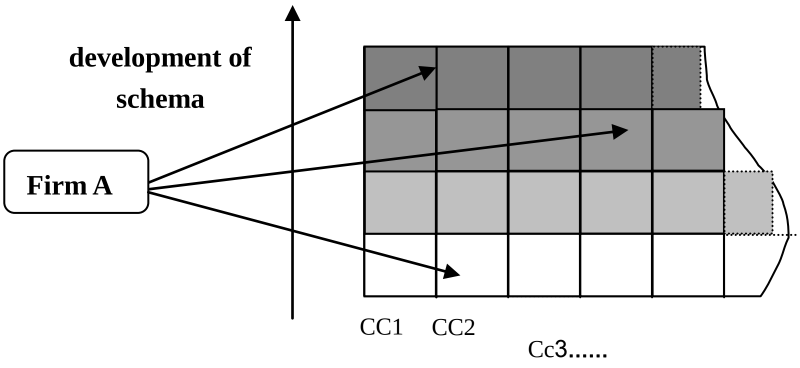


Fig. 1. The Classification of Cognitive Community[2]

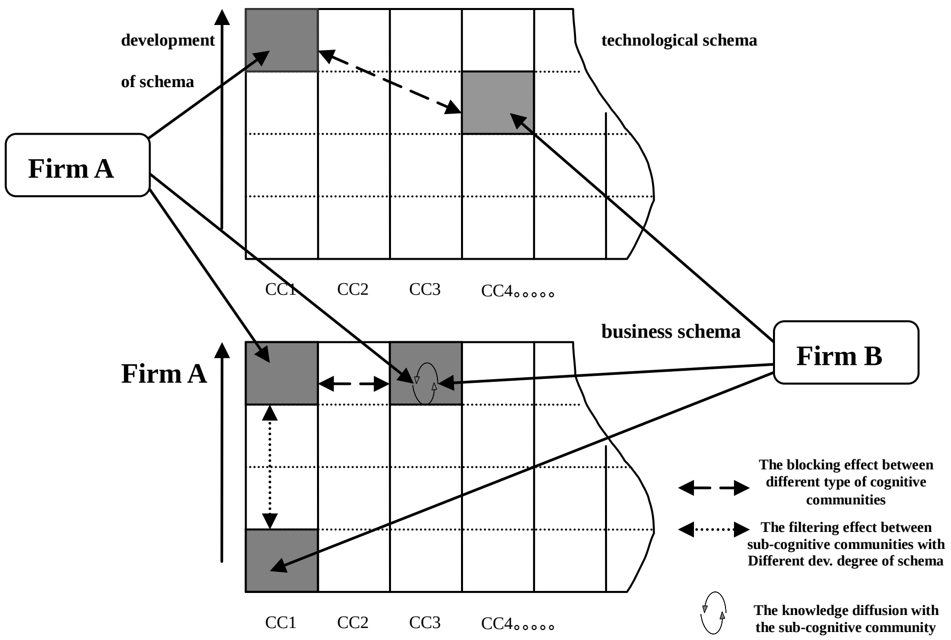


Fig. 2. The Cognitive Community-based Intra-cluster Knowledge Diffusion

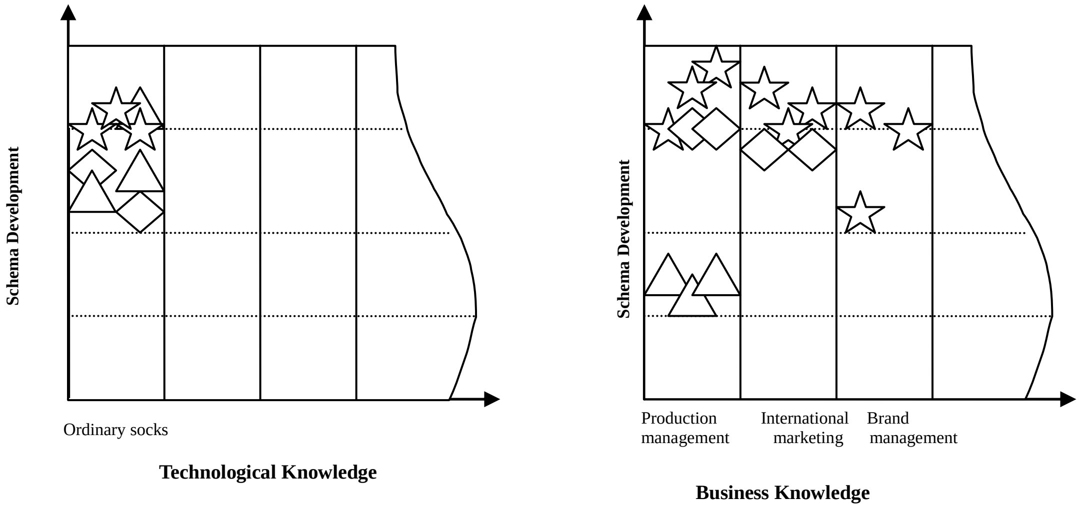


Fig. 3 The Distribution of Knowledge Structure in DSC[6]

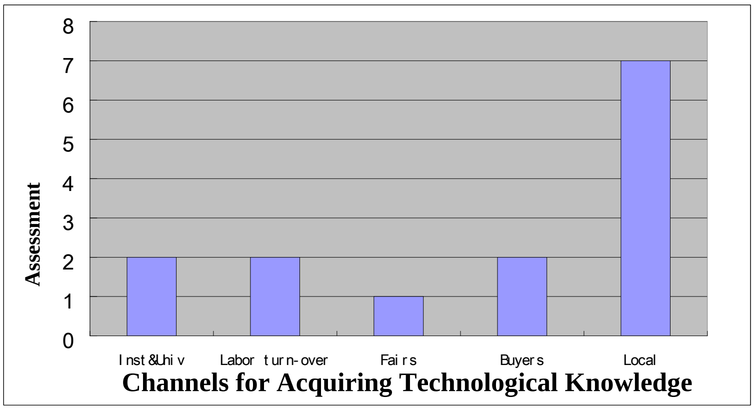


Fig. 4 Main Channels for Acquiring Technological Knowledge[8]

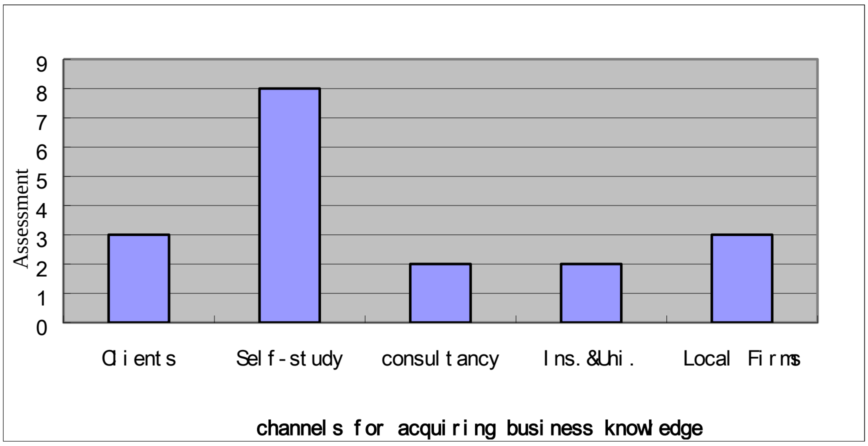


Fig.5 Main Channels for Acquiring Business Knowledge[9]

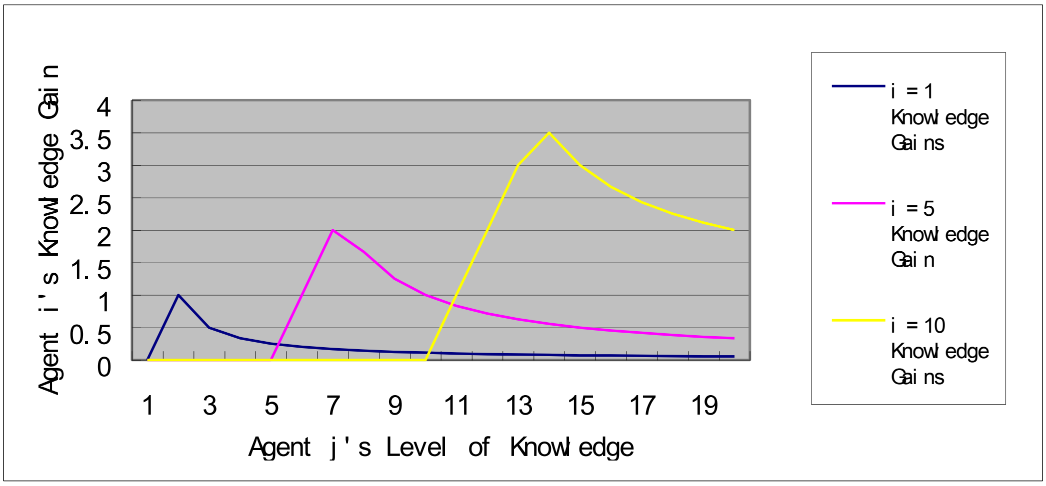


Fig. 6. The Knowledge Gain of Agent i with an Initial Level of Knowledge Equal to 1, 5 and 10

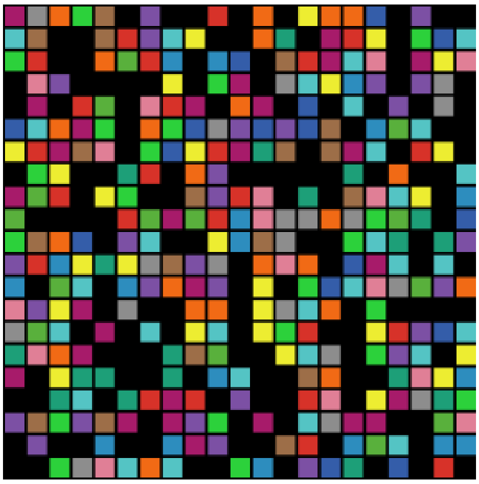
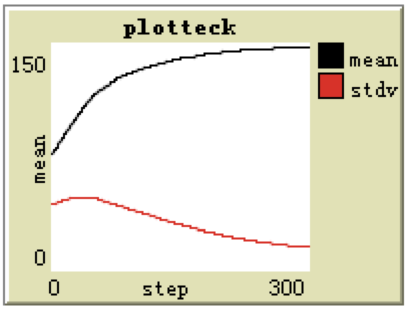


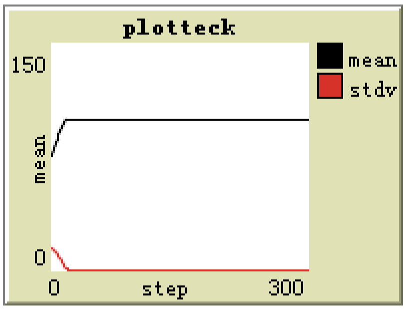
Fig. 7. 300 Agents on the Wrapped Grids



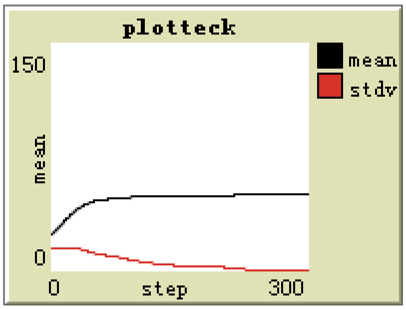
The mean and standard variance

of technological knowledge distribution

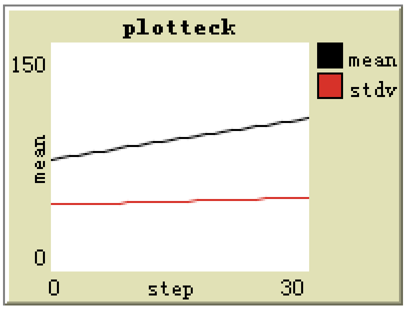
Fig. 8. The Long Term Dynamics of HL Cluster



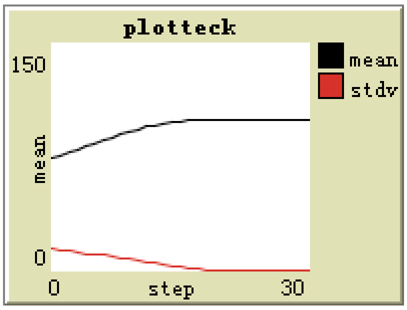
The mean and standard variance
of technological knowledge distribution
Fig. 9. The Long Term Dynamics of HL Cluster



The mean and standard variance
of technological knowledge distribution
Fig. 10. The Long Term Dynamics of LL Cluster



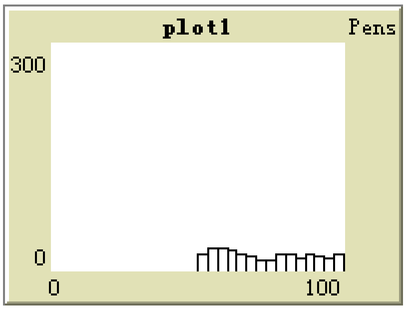
The mean and standard variance
of technological knowledge distribution
Fig. 11. The Short Term Dynamics of HH Cluster



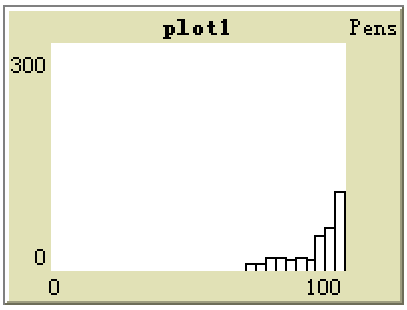
The mean and standard variance

of technological knowledge distribution

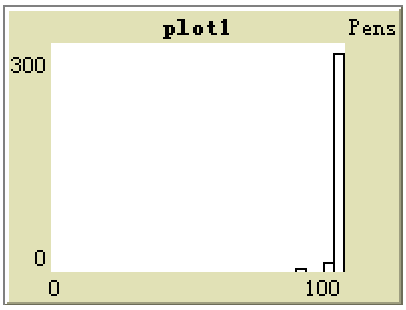
Fig. 12. The Short Term Dynamics of HL Cluster



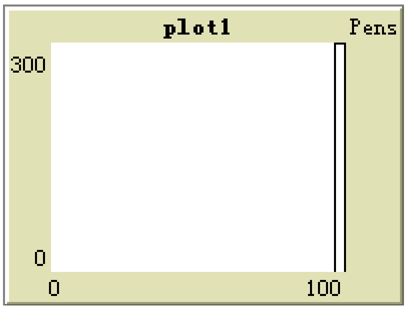
The agents' technological distribution by cycle 0



The agents' technological distribution by cycle 10

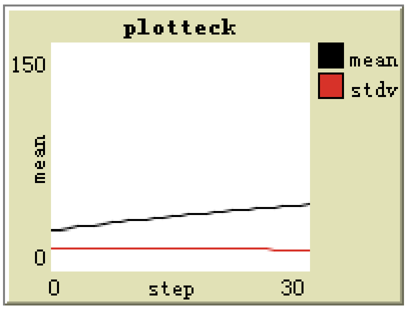


The agents' technological distribution by cycle 20

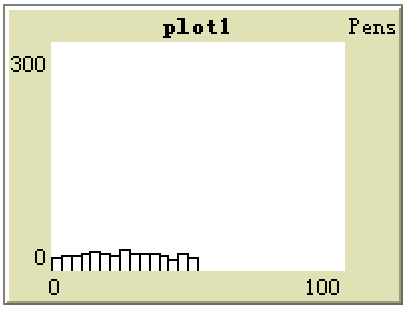


The agents' technological distribution by cycle 30

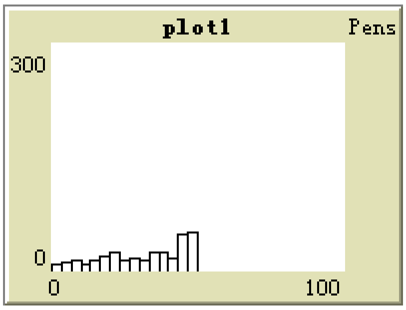
Fig. 13. The Dynamics of Agents' Distribution of Knowledge in the HL Cluster



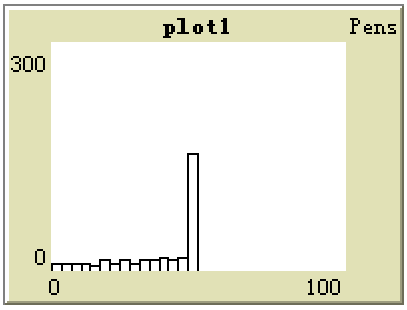
The mean and standard variance
of technological knowledge distribution
Fig. 14. The short term dynamics of LL cluster



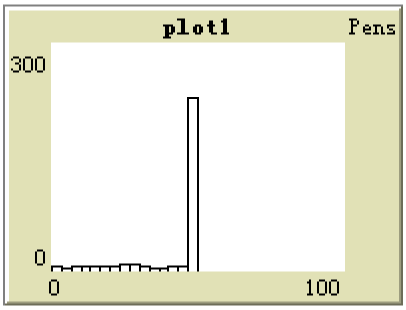
The agents' technological distribution by cycle 0



The agents' technological distribution by cycle 10



The agents' technological distribution by cycle 20



The agents' technological distribution by cycle 30

Fig. 15. The Dynamics of Agents' Distribution of Knowledge in the LL Cluster

Table 1. Summary of the Major Characteristics of the Firms[4]

Firm	Duration in years	Size	Product	With/without brand
WY	>10	Large	Finished socks	yes
AL	>10	Large	Finished socks	yes
BR	>10	large	Finished socks	yes
SWT	>10	medium	Finished socks	no
SBL	>3	medium	Finished socks	no
JA	>10	small	Semi-finished socks	no
JB	>3	small	Semi-finished socks	no
JC	>10	small	Semi-finished socks	no

Table 2. Examples of Data Coding[5]

Coding Category	Example
Types of technology	Our major business is sock-making, part of our production is outsourcing
Level of technology	Our technology is just on average, but we are making rapid progress through efforts.
Technological development strategy	There have been no vast changes in this industry, and the major problem at present is how to raise productivity.
Market orientation	Our major clients are from abroad. We accept foreign orders and subcontract them to other manufacturers
Market development ability	I think we are better at market development than others. Our knowledge about how to conduct foreign trade brings us competitive edge.
Business strategy	We feel that capital, technology and management are very important, and all these aspects must be strengthened for the firm's development.
Communication Channels for technology	We usually turn to local technicians to solve technological problems, but we do this informally. We seldom communicate technology outside Datang.
Communication channels for market	Whether we can get orders depends on our own…. I think knowledge gained from college education to be of great help, such as English and marketing.