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**Ren Lu**

**BI Norwegian Business School**

**Ruikan Zhang**

**Foshan Nanhai Branch**

**Torger Reve**

**BI Norwegian Business School**

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# Relations among Clusters in Six Chinese City Regions

By

Ren Lu

Department of Strategy and Logistics

BI Norwegian Business School

Nydalsveien 37, 0442 Oslo, Norway

Email address: [ren.lu@bi.no](mailto:ren.lu@bi.no)

Ruikan Zhang

Shen Zhen Development Bank, Foshan Nanhai Branch

No44-1 Nanhai Road, 528200 Foshan, Guangdong Province, China

&

Torger Reve

Department of Strategy and Logistics

BI Norwegian Business School

Nydalsveien 37, 0442 Oslo, Norway

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## **Abstract**

Despite the considerable number of papers that have discussed industrial clusters, it is surprising that little research evidence on relations among clusters. This paper collects longitudinal data on three low-tech and two high-tech industrial clusters in six cities in the dynamic Pearl River Delta of the People's Republic of China. The findings provide empirical support to both the MAR model, which argues for the importance of homogenous (specialized) clusters and the Jacobs model, which argues for the importance of heterogeneous (diversified) clusters. Both homogenous and heterogeneous clusters in the same region influence one another's cluster size and economic output.

**Key Words:** homogeneous clusters, heterogeneous clusters, relations among clusters, Pearl River Delta, China

## Introduction

Over the last 20 years, the term “cluster” has become popular, both as an academic term and as a practical strategy used for developing regional economy. In terms of theory, Michael Porter and Paul Krugman paved the road for cluster research. Porter (1990; 1998b) built his famous diamond model, which suggested that clusters can be developed through four aspects (factor, demand, related industries and rivalry). Porter and his followers tested the diamond model many times (e.g., Chobanyan & Leigh, 2006; Moon et al., 1998), showing that the model has predictive power. Krugman (1991a) initiated a paradigm called New Economic Geography (NEG) based on his mathematical “core-periphery” model. NEG differs from traditional economic geography in that it considers that firms agglomerate at the same area because of increasing return and imperfect competition. Since Krugman, the cluster theory has received strong mathematical support. Furthermore, the world has witnessed some actual IT cluster successes, particularly the growth of Silicon Valley during the 1980s (Bresnahan et al., 2001; Ferrary & Granovetter, 2009; Saxenian, 1990), and failures, such as the bursting of the dot-com bubble (Florida & Kenney, 1990; Suire & Vicente, 2009). Clusters can be found in almost any industry, such as life sciences (Gertler & Vinodrai, 2009; Powell *et al.*, 2005), financial industry (Pandit et al., 2001), and motor-sport industry (Henry & Pinch, 2000).

Cluster research has reached “middle age” and needs further development (Fingleton, 2011; Krugman, 2011). At the micro level, people need to combine innovation theories with cluster theories (Cruz & Teixeira, 2010). At the macro level, however, relations among clusters are still a remote topic that has not attracted the attention of scholars to any great degree.

Economic development, particularly urbanisation, has led to the phenomenon of several clusters appearing in the same place simultaneously. A prominent example is Seattle (USA), which has three major industrial clusters (Gray *et al.*, 1996): an aircraft cluster (represented

by Boeing), an IT cluster (represented by Microsoft) and a biotechnology cluster (represented by Fred Hutchinson Cancer Research Centre). These three clusters are located in the same city and share the same labour pool, and contribute knowledge to one another. Meanwhile, when several clusters appear in the same place, they also push up production and living costs, which can lead to a decline in the scales of clusters (Krugman, 1991a; 1991b).

Moreover, there are many examples of competition and collaboration among clusters. For instance, Blundel and Thatcher (2005) described the case of how the yacht manufacturing cluster in South Coast of England gradually declined as its market was eroded by other yacht manufacturing clusters in France, Sweden, and Germany. In the 1990s, the Sinos Valley shoemaking cluster in Brazil had to give up its low-end shoe products in the face of fierce competition from several shoe clusters in China, which had even lower labour costs (Schmitz, 1995). On the other hand, clusters can cooperate with each other. For example, IT clusters in Taiwan and mainland China have invented a specific method of cooperation. Clusters in Taiwan (such as the Hsinchu IT cluster) handle the R&D, while mainland China clusters (such as the Shenzhen IT cluster) receive technologies from Taiwan and manufacture the final products (Chen, 2004; Hsu & Saxenian, 2000).

The existing literature contains two primarily integrated theories that could help a discussion of the relations among clusters. They are the Marshall-Arrow-Romer (Arrow, 1962; Marshall, 1890; Romer, 1986) model (the MAR model) and the Jacobs model (1969) (for more details see Beaudry & Schiffauerova, 2009). The MAR model contends that increasing the level of specialisation of an industry will benefit a local economy, while the Jacobs model argues that locating many various industries in the same place will bring advantages for a local economy. However, both models are situated at the industrial level, which means they only show the relations among individual industries. Because a cluster is a group of related

industries located in the same region (Porter, 1998b), the two models lack the ability to explain the relations among clusters, such as the relations among three clusters in Seattle.

The current study has collected data (the number of firms and the number of gross outputs of clusters) from five types of clusters in six cities in the Pearl River Delta in China to reach three key conclusions regarding cities that have both high-tech clusters and low-tech clusters. Firstly, homogenous clusters benefit from each others' development but heterogeneous clusters weaken this positive effect. Secondly, if one considers only high-tech clusters (as the dependent variables) with several low-tech clusters (as the independent variables), the low-tech clusters lead high-tech clusters to compete in the gross outputs. Thirdly, if one considers only low-tech clusters (as the dependent variables) with several high-tech clusters (as the independent variables), the latter do not change the relations among the former.

The paper makes three contributions. Firstly, traditional cluster studies mainly focus on what happens within a cluster itself, such as a geographically spatial perspective (e.g., Maurseth & Frank, 2009; Zhao, 2003), cluster strategies (e.g., Waits, 2000), innovative ability of clusters (e.g., Baptista, 2000; Simmie, 2004), labour mobility of clusters (e.g., Gittelman, 2006; Power & Lundmark, 2004), and so on. In contrast, this paper investigates the relations among clusters, which is a new way of analyzing cluster phenomena. Secondly, the paper contributes to both the MAR model and the Jacobs model by showing how a group of industries compete or cooperate with each other. Thirdly, the paper offers insights for policy-makers who are interested in adopting a cluster strategy to develop regional economies (Newlands, 2003; Teigland & Lindqvist, 2007).

The remainder of the paper is organised as follows. Section 2 provides the theoretical background, as well as three hypotheses, and Section 3 is the methodology part, which contains the research setting, variables and testing model. Section 4 presents the results of the model, while discussions and conclusions are offered in Section 5.

## **Theoretic Background and Hypotheses**

This subsection briefly defines a cluster. Subsequently, as the empirical data contains two categories – high-tech and low-tech clusters – these two concepts are also defined.

While different scholars have defined clusters in different ways (e.g., Rosenfeld, 1997; Schmitz, 1995), the best known definition is that of Michael Porter (1998b, p.196), who defined a cluster as “Geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (for example, universities, standards agencies, and trade associations) in particular fields that compete but also co-operate”. For example, the most famous IT cluster in the world is California’s Silicon Valley, which is the base for companies such as Hewlett Packard, National Semiconductor, Intel, AMD, Oracle, Apple, Cisco Systems, Yahoo!, eBay and Google, and which created 1.15 million jobs and investments of US\$111 billion from 1995 to 2005 (Ferrary & Granovetter, 2009).

Although many scholars have their own definitions of clusters, two essential aspects of the definition will remain constant. Firstly, cluster members (such as firms, cluster initiatives, research institutes, etc.) must be linked in some way. Relations among cluster members can either be vertical (suppliers-customers relations) or horizontal (competition relation or complementary sharing a common set of knowledge). Moreover, most of these linkages involve social relationships or networks that can generate benefits for cluster firms (Martin & Sunley, 2003, p.10). Secondly, clusters have geographical boundaries, which means that firms belonging to a focal cluster should be located in a certainly geographical space. Locating in proximity “encourages the formation of, and enhances the value-creating benefits arising from, networks of interaction between firms” (ibid, p.10).

There are many ways to classify clusters (e.g., Malmberg & Maskell, 2002). The present paper categorises clusters into high-tech and low-tech clusters. Porter (1998a, p.80) plays

down the high-tech vs. low-tech typology, and argues that “all industries can employ advanced technology and all industries can be knowledge intensive”. Nonetheless, the reality in developing countries is that many industries, such as the textile, shoemaking, and the toy manufacturing industries, still rely heavily on labour-intensive work (Zeng, 2010). Indeed, most developing countries still compete on global markets without depending on advanced knowledge or process innovation; instead, they rely on economies of scale, in the form of low skilled workers and low wage levels (e.g., Ng, 2002; 2003). Therefore, this paper argues that the dichotomy of high-tech and low-tech clusters is a simple but useful way to study clusters and can at least be applied to many poor and developing countries. In addition, classifying industries into high-tech and low-tech remains a popular method that is adopted by mainstream scholars of clusters. This method is feasible, needing only to draw on industries’ classification. For example, in their investigation of four Norwegian clusters, Onsager et al. (2007, p.553) noted that “the high tech industries, if often operationalized and delimited to manufacturing industries with comparatively high R&D intensity, and to service industries that are large users of advanced embodied technology and that have comparatively a large amount of workers with higher education”. Onsager et al. went on to mention that both OECD and Norway have classifications of knowledge-intensive service that scholars can use to conduct relevant studies (ibid, p.566). Henderson et al.’s (1995) study of American manufacturing industries classified “primary metals, machinery, electrical machinery, transport equipment, and instruments” as low tech industries and “computer, electronic components, and medical equipment” as high-tech industries.

The present paper uses three features to identify high-tech intensive clusters and low-tech clusters. The first feature is capital investment. Because they rely on knowledge and innovation, except investment in fixed assets, high-tech clusters also need money to invest in new technologies to satisfy and guide consumers’ requirements. A significant example can be

seen in many university-core clusters, in which universities created new products and let consumers accept their goods (Patton & Kenney, 2010). In low-tech clusters, however, the money is mainly spent on paying workers' wages and on fixed maintenance fees of machines, but not on R&D (Zeng, 2010). The second feature is labour investment. High-tech clusters need educated labour pools, while low-tech clusters have less specific requirements regarding educated labour. Furthermore, high-tech clusters generally offer their employees higher wages than low-tech clusters, while high-tech clusters offer fewer jobs than low-tech clusters. The third feature is that these two kinds of clusters have different markets. Generally speaking, the high-tech clusters are targeted at high-end products, such as aircrafts, advanced medicines, IT and weapons (Onsager *et al.*, 2007). High-tech products are normally accompanied by high unit prices, but the total consumption volume is low. The markets of low-tech clusters, in contrast, are targeted at high volume consumption markets. These goods are cheaper than high-tech products in terms of unit price, but the volume of total consumption is high.

### *Relations among Regionally Homogenous Clusters in the Same Region*

Based on the above-mentioned identification of high-tech and low-tech clusters, this paper uses the terms "homogenous" and "heterogeneous" to describe the relations among clusters. Homogenous clusters are those that use the same technology (that is, either high tech or low tech). Heterogeneous clusters, by contrast, are those clusters that use different technologies (that is, a region that has both high-tech clusters and low-tech clusters). This subsection discusses homogenous clusters.

At the cluster level, several homogenous clusters located in the same place have certain advantages in terms of expanding their business. Firstly, homogenous clusters generate a common labour pool. This phenomenon can easily be understood in relations among low-tech clusters. The main reason is that low-tech clusters have few requirements regarding educated

employees. Therefore, one person can serve every cluster in the region. An example is the Shenzhen Special Economic Zone (China) in the 1990s. At that time, like many exporting processing zones, Shenzhen involved many low-tech clusters, such as a textile cluster, a shoe cluster and a food-processing cluster (Zeng, 2010). A worker who moved from inland China to Shenzhen could quickly find a job in those clusters. Because many factories in China had assembly lines, an inexperienced person only required a few hours of training before being able to start work. In terms of high-tech clusters, although well educated people normally do specific jobs, they are more able to extend their working field (Harrison *et al.*, 2004). In Seattle, for instance, an IT engineer can write software for an IT company, as well as for an aircraft firm. Furthermore, a talent accessed to various contexts has more innovative capabilities, and many scientific breakthroughs often appear across disciplines (Gittelman, 2006).

Secondly, a region with homogenous clusters can cultivate the same regional tacit knowledge. For example, Goss and Vozikis (1994, p.295) argued that, in high-tech industries, “in areas where there is a concentration of high tech firms, there are more spillover effects reflected in higher value created per worker”. There are two reasons for this: (1) people with similar education background can easily communicate and interact with each other, and (2) tacit knowledge is spread in the region, which increases the attractiveness for outsiders (Lambooy, 2010; Simmie & Hart, 1999). Moreover, local tacit knowledge is helpful for developing local economies. Varga and Schalk (2004) studied data on Hungary’s 19 counties between 1998 and 2000, finding that regional growth rate is significantly affected by tacit knowledge, and that knowledge spillovers are bounded spatially.

Thirdly, a region with homogenous clusters has advantages in terms of creating a common market. “Agglomeration among retail or service firms can heighten demand by attracting more customers than the sum of those that the agglomerating firms would attract individually”

(Kalnins & Chung, 2004, p.690). As mentioned above, tacit knowledge is shared among all regionally homogenous clusters; when one cluster develops a new market, other clusters might follow the same way. As Porter (1996, p.63) noted, “rivals can quickly imitate management techniques, new technologies, input improvements, and superior ways of meeting customers’ needs”. Porter’s argument can be applied to relations among homogenous clusters in the same region. For example, when a toy cluster in Wenzhou (China) opened up a market in the US, other homogenous clusters in Wenzhou soon followed the same or similar marketing channels and business models to conduct business with the US.

At the firm level, a region with homogenous clusters creates several advantages for every firm in the region. Firstly, each firm in the region can enjoy the stability of local networks (Staber, 2011; Westlund & Adam, 2010), which can be formal or informal. Considering the formal networks, according to Coleman (1988)’s dense network theory, cluster firms might start by building dense networks within the cluster and then expand their relations with “peripheral” firms located in the same region. Such dense networks are stable when firms maintain close geographical proximity, and weak ties are strongly affected by spatial distance (Rutten *et al.*, 2010). By doing this, firms have the chance to communicate with each other, and they establish internal mutual trust. Schutjens and Völker’s (2010) study of 385 Germany enterprises found that the enterprises’ economic performance is tightly tied to the local network.

Secondly, homogenous clusters help established firms create spin-offs. Entrepreneurs who have creative ideas but do not receive support from their incumbent firms will often set up their own firms close to their working firms (Harrison *et al.*, 2004). May *et al.* (2001, p.374) argued that “founders typically set up new enterprises close to their place of residence”. Oakey *et al.* (2001, p.412) studied the British non-broadcast visual communications industry, finding that “local spin-off may explain the physical intensity of clusters, both in terms of a

reluctance to move far when relocating, and a preference for locating near to the firm from which new entrepreneurs had ‘spun-off’”. Most of those firms establish a business that differs from that of the incumbent firms. They combine their knowledge with other homogenous clusters. By doing this, the entrepreneurs can still draw on their local networks, as well as other useful resources. Klepper’s (2002) investigation of data on American automobile industries from 1895 to 1966 revealed that the firms that had diversified from bicycles, engines, carriages and wagons had been the ones to survive in the automobile industry.

Last but not least, the higher the number of related industries in a region, the more opportunities there are to enhance regional growth (Boschma & Frenken, 2011). For example, Britton et al. (2009) presented a business model of Canadian New Media industries, in which there are many temporary projects that need a combination of different resources to complete (such as three dimensional animation advertisement). Delgado et al. (2010, p.4) studied 41 clusters in the U.S., finding that “at the same time, the growth of region-industry employment is increasing in the size and the strength of regional cluster to which that industry belongs, the size and strength of related clusters, and the size and strength of common clusters in neighbouring regions. We also find that a strong regional cluster facilitates the creation of new industries within that cluster”. Moreover, in the United Kingdom, the automobile companies that had the highest survival rates were those who engaged in many related activities (Boschma & Wenting, 2007).

**Hypothesis 1:** Homogenous clusters in the same region positively influence each other’s size and economic output.

### *Relations among Regionally Heterogeneous Clusters in the Same Region*

As mentioned above, a region with heterogeneous clusters is one that has both high-tech and low-tech clusters. Although Jacobs’ (1969) theory is primarily applied to discuss relations

among diversified industries, it is a good departure point for discussing issues about heterogeneous clusters.

Jacobs (1969) argued that the most critical resources pushing the development of an industry come from outside the industry itself, rather than from within the industry (such as internal R&D). Heterogeneous clusters in the same region can generate various forms of knowledge innovation and economic growth. The innovative research and experimentation is facilitated by the exchange of complementary knowledge among various firms and economic agents. An economy with diversity naturally has the ability to push knowledge exchange and form new fields (Beaudry & Schiffauerova, 2009). In addition, Neffke et al. (2011) claimed that the more diversification a regional economy has, the more likely it is that the region can create beneficial inter-industry knowledge and product combinations. Moreover, firms in a region that has industrial diversity have more access to stable demand conditions and a wider range of local input substitutes, which helps them avoid price fluctuations in inputs and in outputs (ibid).

Regions, particularly those in developing countries, generally start with low-tech industries and transfer to high-tech industries after the regions are sufficiently developed (e.g., Zeng, 2010). High-tech clusters have a positive influence on low-tech clusters because high-tech clusters always bring high qualified human resources and intensive capital support. On the other hand, low-tech clusters create accumulation of wealth, including institutions, infrastructures and other facilities for the development of high-tech clusters.

In real life, several cases have laid out the relations among heterogeneous clusters. Neffke et al. (2011) studied 12 manufacturing industries in 70 Swedish cities over the period 1974–2004, showing that young clusters benefit from diversity in a region with heterogeneous clusters, while mature clusters might experience losses and declines because of the diversity. Low-tech clusters that are heavily dependent on low taxes and cheap labour will have less

competitiveness in their recruitment efforts than high-tech clusters (Galbraith, 1985). Higgins et al. (2006) used county level data from 3058 US counties to study economic growth and measure the speed of convergence, concluding that convergence rates vary among the counties. Bostic et al. (1997, p.41) argued that “capital (labour)-intensive cities should induce more labour (capital) inflow than less capital (labour)-intensive cities”. Based on American industrial data for 1880 and 1890, Bostic et al. (1997, p.49) concluded that “intra-industry agglomeration economies have a greater positive impact on capital than labour accumulation, while the reverse is true for inter-industry agglomeration economies”. Furthermore, Dumais et al. (2002, p.202) investigated more than 300,000 manufacturing establishments in the United States; their results are consistent with Jacobs’ view that “new plant births tend to act to reduce geographic concentration”. Asheim and Coenen (2005) studied five clusters in Nordic countries and found that the various clusters used different strategies. Low-tech clusters should strengthen their industrial specialisation, but high-tech clusters should have co-operation and interaction with knowledge providers (such as universities, research institutes, etc).

Regional industrial identity (e.g., Pólos *et al.*, 2002) is another way of thinking about heterogeneous clusters. Regional identity is obtained “not only from the personal identifications of individuals, which affect their perceptions of similarity or membership in groups, organizations, or other social entities, but also from the shared understandings of audiences, especially external audiences, about key features of the social entities” (Romanelli & Khessina, 2005, p.345). For example, leading firms create regional identity, through which the region receives advanced technologies, talents and capital (Giblin, 2011). From a regional identity perspective, Romanelli and Khessina (2005) proposed several propositions that are useful for explaining heterogeneous clusters. Firstly, regions with multiple related industry clusters will attract and retain more heterogeneous resources than regions with multiple

unrelated industry clusters (ibid, p.353). Secondly, the focus of a region's identity affects the heterogeneity of resources that flow into the region. Regions with narrowly focused identities attract more homogeneous resources than regions with generalised identities (ibid, p.349).

**Hypothesis 2a:** If a region that is dominated by one type of cluster (either high-tech or low-tech) has few heterogeneous clusters, these heterogeneous clusters positive influence each other's size and economic output.

If a region has many heterogeneous clusters, it will cause a "congestion effect", which means that the costs increase sharply. Neffke et al. (2011, p.52) argued that "local diversity is beneficial to a region, as long as it is not too spread out across too many different industries". Gordon and McCann (2005, p.530) used the example of London, a city with advantages related to innovation, business and education. It offers high-quality services that are not available in other places because of its high degree of specialisation and novelty. However, London also suffers from high transaction costs, such as space costs, price level and labour costs. Storper (2011, p.337) argued that housing prices and housing supply, play a critical role in controlling cluster development because they limit population growth by driving nominal wages up but real wages down. However, this effect will not happen in homogeneous clusters. Glaeser et al. (1992, p.1129) analysed 170 of the largest cities in the United States and their conclusions are: Firstly, when an industry is over-represented in a city, that industry will have a low growth rate in terms of employment. Secondly, "industries grow faster in cities in which firms in those industries are smaller than the national average size of firms in that industry", and thirdly, "city industries grow faster when the rest of the city is less specialized".

**Hypothesis 2b:** If a region consists of many heterogeneous clusters simultaneously, the heterogeneous clusters negatively influence each other's size and economic output.

# Methodology

## *Research Background: Pearl River Delta in China*

The hypotheses are tested using data from the Pearl River Delta (PRD). Figure 1 shows the PRD’s geographical location.

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Insert Figure 1 about here  
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The PRD, which involves nine prefectures of Guangdong Province (Guangzhou, Shenzhen, Zhuhai, Dongguan, Zhongshan, Foshan, Huizhou, Jiangmen, and Zhaoqing, and the Special Administrative Region of Hong Kong and Macau), is a dense network of cities. Surrounding the Pearl River estuary, where the river flows into the South China Sea, more than 120 million people live in the PRD.

From an economic perspective, “The PRD has been the most economically dynamic region of the People’s Republic of China since the launch of China’s reform programme in 1979. In 1991, almost 50% of foreign investment in China was in Guangdong, and 40% in the PRD. By 2001 its GDP rose to just over US\$100 billion and it was experiencing an annual growth rate more than three percentage points above the national growth rate. Since the onset of China’s reform program, the Pearl River Delta Economic Zone has been the fastest growing portion of the fastest growing province in the fastest growing large economy in the world. The Pearl River Delta has become the world's workshop and is a major manufacturing base for products such as electronic products, toys, garments and textiles, plastic products, and a range of other goods. Much of this output is invested by foreign entities and is geared for the export market. The Pearl River Delta Economic Zone accounts for approximately one third of China's trade value. Nearly five percent of the world’s goods were produced in the Greater Pearl River Delta in 2001, with a total export value of US\$ 289 billion” (Wikipedia, accessed in March 2011, available at [http://en.wikipedia.org/wiki/Pearl\\_River\\_Delta](http://en.wikipedia.org/wiki/Pearl_River_Delta)).

Twenty-one years of longitudinal data was collected from the Guangdong Provincially Annual Year Statistical Book (1989–2009) regarding three low-tech clusters (the textile and garments cluster, the food and beverage cluster, and the logging and paper-making cluster) and two high-tech clusters (the electronic information cluster and the electric equipment and special purposes equipment cluster) in six PRD cities (Dongguan, Zhongshan, Foshan, Guangzhou, Jiangmen, and Shenzhen). This data was used to test the relations among regionally clusters in terms of cluster size and economic output.

### *Measures*

There are many ways to measure a scale of a cluster. One example is the locational Gini coefficient that Krugman (1991a, p.129) used to calculate the US's three digital industries. Ellison and Glaeser (1997) improved Krugman's measure by advancing the Ellison-Glaeser index (EG index). Essentially, these two measures do not vary greatly. Besides, qualitative research has Multisectoral Qualitative Analysis (Bryan *et al.*, 2005). Nevertheless, the most simple but popular measurement is to calculate Location Quotients (Simmie & Sennett, 1999), the equation for which is:

$$LQ = \frac{\text{a region employment sector X}}{\text{total region employment}} \bigg/ \frac{\text{a nation employment sector X}}{\text{total nation employment}}$$

If the LQ is greater than 1, it means that a focal region has a larger proportion of employees for a sector. Thus, this focal region has cluster effect. "The LQ approach can reveal whether a reference region has a relatively high share of sectoral employment compared with the national average" (Bryan *et al.*, 2005, p.637). Although this measure is highly sensitive to the size of the region, it is a better way to capture the image of a cluster than the industry proportion in the region (Beaudry & Schiffauerova, 2009).

Although measuring LQ though employment is often seen in cluster research (Bryan *et al.*, 2005), the essence of LQ is to compare a relative share of one or several industries between a

small region and a large region. Therefore, a cluster can be measured by other kinds of parameters, such as “regional GDP or living standards” (Lorenzen, 2005, p.204). Bearing this in mind, and considering that the Guangdong Provincially Annual Yearbooks do not provide information about employment of every industrial sector in each city in detail, this paper compared different clusters in terms of numbers of firms and the value of outputs of each cluster (this method is mentioned in Feldman & Audretsch, 1999). The two equations applied in this paper are presented here.

$$LQ_f = \frac{a \text{ region firm nubmers sector X}}{\text{total region firm nubmers}} \bigg/ \frac{a \text{ nation firm numbers sector X}}{\text{total nation firm nubmers}}$$

$$LQ_g = \frac{a \text{ region industiral output values sector X}}{\text{total region industrial output values}} \bigg/ \frac{a \text{ nation industrial output values sector X}}{\text{total nation inudstrial output values}}$$

*Variables*

The measure of clusters applied in this paper follows the same method of Porter (2003), which studied regional clusters in the United States. Because the present study uses the Chinese data, it follows Hong and Fu’s (2011) method, which classifies high-tech industries based on the State Statistical Bureau of China’s standard. Therefore, according to the Annual Yearbook’s classification, this study categorises the electronic information cluster, and the electric equipment and special purposes equipment cluster as high-tech clusters. The textile and garments cluster, the food and beverage cluster, and the logging and paper-making cluster are classified into traditional low-tech clusters. The Table 1 gives more details about these clusters.

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 Insert Table 1 about here  
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In order to calculate the LQs, all relevant data shown in the equations was collected. More concretely, data was collected on the number of firms belonging to each cluster, as well as how much gross output value each cluster generated. To calculate the LQ, data was also

collected about the total number of firms in each city, as well as Guangdong province overall, and the gross output value of each city had and of Guangdong province. The three following control variables were also checked: population, gross output value of industry by each city, and average wage by each city.

Two things about the data should be noted. Firstly, because China is still developing its statistical database, there is a lack of detailed data about all kinds of firms. Thus, this paper followed Hong and Fu’s (2011, p.2344) method, which only investigated enterprises above “a designated size (which means firms with annual sales of over 5 million Chinese Yuan)”. Secondly, there are some missing values in the database – specifically, no population data was available for 2000 and 2002. However, because the database has 1890 items and missed fewer than 20, this will not affect the overall result. Braunerhjelm and Borgman (2004, p.933) encountered a similar problem during their study of Sweden manufacturing industries; they noted that “the richness of the database and the relatively limited occurrence of missing values imply that the impact on the statistics presented is negligible”. Furthermore, the population is a very stable value. The present paper simply uses the mean values of 1999 and 2001 to represent the 2000 population, and the mean value of 2001 and 2003 to represent the 2002 population.

**Results**

Once all the data was collected, the LQ was calculated for each cluster in the six cities from 1989 to 2009. Table 2 reports the means, standard deviations and correlations among all the variables.

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Insert Table 2 about here  
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Table 2 shows that four kinds of clusters had an LQ greater than 1, which means that those four kinds of clusters appeared in the six cities. The LQ of the food and beverage cluster is

0.748 in terms of the number of firms, and 0.934 in terms of the gross output value. This means that although the six cities had fewer firms processing foods, they produced more value than they were supposed to have.

Because this paper does not specifically discuss statistical problems, the longitudinal data was analysed using a multilevel linear model (MLM), which is a relatively sophisticated method. The mathematical essences and mechanisms of the MLM are shown in many textbooks (e.g., Hox, 2002; Snijders & Bosker, 1999). By running Lisrel8.80, which places a city at the second level, the paper treats the values of LQs as independent or dependent variables in different situations.

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Insert Table 3  
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Table 3 simply includes control variables. Surprisingly, although the regional gross industrial output values and regional average wages have significant relations with scales of clusters, the correlated effects are very low. Population has a negative impact on the scales of several clusters.

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Insert Table 4 and 5 about here  
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Tables 4 and 5 lay out the relations among homogenous clusters. Table 4, which portrays the relations among low tech clusters, reveals that clusters of textile and garment have positive relations with the other two low-tech clusters in terms of the number of firms (NF). Meanwhile, the clusters of logging and papermaking are positively related to the other two clusters in terms of industrial output values (IOV). Table 5, however, reflects that the two high-tech clusters are positively related in terms of NF, but have no relations in terms of IOV. However, it should be noted that although not every cluster can influence other homogenous clusters in the same region in every aspect, the interaction is positive when two homogenous clusters interact with each other. These findings largely support Hypothesis 1.

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Insert Table 6 and 7 about here  
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Tables 6 and 7 indicate the way in which one cluster relates to several heterogeneous clusters. Table 6, which shows how low-tech clusters influence two high-tech clusters, respectively, indicates that low-tech clusters almost always positively influence the electronic information cluster, except that the food and beverage cluster was not related to EIC in terms of IOV. The electric equipment and special purposes equipment clusters (PEC) are also positively related to low-tech clusters in various aspects. Table 7 uncovers how high-tech clusters influence low-tech clusters. The reality is that clusters of textiles and garments (CTG) are fully influenced by both EIC and PEC in a positive way. Logging and papermaking clusters are almost identical to CTG, except that PEC has no relation with CTG in terms of IOV. Food and beverage clusters are positively related to EIC in terms of NF, and positively related to PEC in terms of IOV. These findings largely support Hypothesis 2a.

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Insert Table 8 about here  
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Table 8 is an integrated model that tested all five kinds of clusters simultaneously. This table indicates that the relation between heterogeneous clusters does change significantly, which means that the conclusion in Tables 6 and 7 still exists when a region has several high-tech and low-tech clusters simultaneously. The relations among homogenous clusters do not change in terms of low-tech clusters, as shown in Table 4. The relation between EIC and PEC in terms of NF does not change. However, the relation between EIC and PEC in terms of IOV changes from a positive effect to a negative effect. This means that EIC and PEC tend to agglomerate in the same place, even though they might cause each other to produce lower industrial outputs. In summary, Table 8 does not support Hypothesis 2b in low-tech clusters, and Hypothesis 2b is only satisfied when examining relations among high tech clusters in terms of IOV.

## **Discussion and Conclusion**

Based on the MAR model and the Jacobs model, this paper finds that if only homogeneous clusters are considered, and if relations exist among homogenous clusters, the relations are always positive. On one hand, homogenous clusters push each other to process their original fields; in particular, high-tech homogenous clusters that use similar technologies in the same region can share tacit knowledge and draw on technologies in other high-tech clusters. On the other hand, low-tech clusters in the same region can share many basic conditions, such as labour pool, business environment, etc.

In this situation, if only one high- (or low-) tech cluster is considered with several low- (high-) tech clusters, the relations among heterogeneous clusters are mainly positive. The phenomenon can be explained as follows: when a high-tech cluster enters a region with several low-tech clusters, the high-tech cluster brings new knowledge, capital and qualified people to the region, and then benefits the development of low-tech clusters. On the contrary, when a low-tech cluster enters a region that has several high-tech clusters, the low-tech cluster brings more job opportunities for the region.

If a region simultaneously has many heterogeneous clusters, the relations among low-tech clusters and the influences that the high-tech clusters have on the low-tech clusters do not vary. However, low-tech clusters also led to EIC and PEC declining their industrial output value. To some extent, this indicates that when a region has several low tech clusters, the region does is able, to some degree, to attract more high-tech firms in the region. However, not every high-tech firm benefits from their homogenous clusters.

The testing of three control variables led to several additional findings. The regression models in the paper reveal that population has little influence on scales of clusters. Although the population in the sample kept increasing over the last 21 years, the LQ in five clusters did not change as much. Furthermore, like population, gross industrial output value has almost no

influence on scales of clusters. Average wage, however, definitely has an influence on scales of clusters, albeit a small one. In summary, all three control variables have relatively little influence on relations among clusters.

Built on the regression models, some further explanation of our hypotheses is provided. Why were Hypothesis 1 and Hypothesis 2a, which seems to be two conflicted hypotheses derived from the MAR theory and the Jacobs theory, respectively, both supported? This paper argues that the macro economy background may provide one of the answers to this question. All empirical data used in the present paper is from PRD China in the last 21 years. The PRD, the first area that China opened up to the world, is the most economically prosperous area in mainland China. Over the last 30 years, China achieved GDP growth of approximately 10 percent every year, but the PRD's rate was as much as two or three percent higher than China's overall annual growth rate. The PRD development model – low-tech clusters were processed first and then high-tech clusters appeared and absorbed more resources for further development – is a typical model that is seen in many developing countries. Of course, regardless of the kind of clusters the PRD had, in China it relied on an enormous pool of cheap labour. Thus, the pursuit of economies of scale is inevitable. The economy of scale of each cluster undoubtedly creates more jobs, while it also leads to more specialised clusters. This is why the MAR effect was observed in the regression model. From the diversification perspective, the so-called “increasing return” effect (Krugman, 1991a) occurred. Because the PRD had a better economy than the cities in inland China, people moved to the PRD for better life. The newcomers were involved both as highly qualified and low qualified human resources. Obviously, people with different qualities and skills will end up doing different jobs. Regardless of what they do, however, they objectively “generated” more diversified firms and more local output values.

Hypothesis 2b did not receive sufficient empirical support. Nonetheless, the paper proposes that the congestion effect still exists. When a region has an increasing number of clusters, the relations among incumbent clusters become weaker – although they are not qualitative changes (from positive relations to negative relations and vice versa). Thus, the congestion effect does exist to some extent but, because China is in the upswing phase in terms of economy, this congestion effect is not as significant as suggested in Hypothesis 2b.

One point deserves further comment. Although three control variables continually increased in the cities over the last 21 years, the LQ values of five clusters did not vary so greatly. This indicates that the absolute scales of clusters have grown in the period under investigation but the comparative scales of the five types of clusters did not change. Furthermore, the paper highlights (through Table 3) that population, local industrial outputs and average wages influence clusters' comparative scales, but that such influences are quite small and limited.

In summary, the paper finds that, during the phase of economic growth (1989-2010), the PRD actually experienced the MAR effect and the Jacobs effect simultaneously. Additional empirical research is needed to verify that whether these research findings apply also to other regions in China. Perhaps this doubts that cluster effect is one of several factors behind the economic development success of China.

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**Table 1: Information about Testing Clusters**

Type	Cluster Name	Abbreviation	Involving which industries
High-tech cluster	<b>Electronic information cluster</b>	EIC	the electronic and telecommunications sector
High-tech cluster	Electric equipment and special <b>purposes equipment cluster</b>	PEC	the special purposes equipment sector, the electric equipment and machinery sector, and the instruments, meters, cultural and clerical manufacturing sector
Low-tech cluster	<b>Cluster of textile and garments</b>	CTG	textile industry, the garments and other fibre products sector and the chemical fibre sector
Low-tech cluster	<b>Cluster of food and beverage</b>	CFB	the food processing, food production, beverage production, and tobacco processing sectors
Low-tech cluster	<b>Cluster of logging and paper-making</b>	CLP	the logging and transport of timber and bamboo sector, the timber processing, bamboo, cane, palm fibre and straw products sector, and the papermaking and paper products sector

**Table 2: Means, standard deviations and correlations.**

Variable	Mean	St. Dev.	Minimum	Maximum	EIC <sub>f</sub>	EIC <sub>g</sub>	PEC <sub>f</sub>	PEC <sub>g</sub>	CTG <sub>f</sub>	CTG <sub>g</sub>	CFB <sub>f</sub>	CFB <sub>g</sub>	CLP <sub>f</sub>	CLP <sub>g</sub>	POPU	GOVI	AW
EIC <sub>f</sub>	1.403	1.147	0.273	5.645	1.000												
EIC <sub>g</sub>	1.038	1.146	0.014	5.899	0.921	1.000											
PEC <sub>f</sub>	1.297	0.346	0.726	2.319	0.452	0.339	1.000										
PEC <sub>g</sub>	1.232	0.580	0.472	3.451	-0.308	-0.296	0.352	1.000									
CTG <sub>f</sub>	1.141	0.274	0.472	2.278	0.063	-0.060	0.154	0.030	1.000								
CTG <sub>g</sub>	1.219	0.593	0.214	2.756	-0.530	-0.453	-0.358	0.152	0.372	1.000							
CFB <sub>f</sub>	0.748	0.271	0.240	1.573	-0.532	-0.570	-0.299	0.081	0.162	0.416	1.000						
CFB <sub>g</sub>	0.934	0.354	0.290	2.339	-0.377	-0.407	-0.315	-0.005	0.201	0.173	0.471	1.000					
CLP <sub>f</sub>	1.153	0.354	0.657	2.597	0.660	0.585	0.364	-0.298	0.323	-0.328	0.562	-0.161	1.000				
CLP <sub>g</sub>	1.315	0.530	0.539	2.836	0.034	-0.008	-0.013	0.057	0.495	0.336	0.359	0.043	0.399	1.000			
POPU	2.182	1.884	0.278	7.946	-0.341	-0.347	-0.403	-0.317	-0.171	-0.138	0.215	0.460	-0.221	-0.298	1.000		
GOVI	156.4	197.9	3.934	913.821	-0.024	0.004	-0.248	-0.271	-0.516	-0.350	0.013	0.097	-0.238	-0.420	0.582	1.000	
AW	16471.4	11637.7	2601	49054	-0.039	-0.022	-0.250	-0.217	-0.446	-0.212	0.164	0.011	-0.201	-0.176	0.485	0.873	1.000

EIC<sub>f</sub>: LQ of Electronic Information Cluster in terms of numbers of firms. EIC<sub>g</sub>: LQ of EIC in terms of gross output value.

PEC<sub>f</sub>: LQ of Electric Equipment and PECcial Purposes Equipment (PEC) cluster in terms of numbers of firms. PEC<sub>g</sub>: LQ of PEC in terms of gross output value.

CTG<sub>f</sub>: LQ of Cluster of Textile and Garments (CTG) in terms of numbers of firms. CTG<sub>g</sub>: LQ of CTG in terms of gross output value.

CFB<sub>f</sub>: LQ of Cluster of Food and Beverage (CFB) in terms of numbers of firms. CFB<sub>g</sub>: LQ of CFB in terms of gross output value.

CLP<sub>f</sub>: LQ of Cluster of Logging and Papermaking (CLP) in terms of numbers of firms. CLP<sub>g</sub>: LQ of CLP in terms of gross output value.

POPU: (Control variable) Population (in million).

GOVI: (Control variable) Gross output value of industry by each city (in billion Chinese Yuan).

AW: (Control variable) Average wage by each city (Yuan).

**Table 3: Regression Coefficients (Control Variables only).**

	POPU	GOVI	AW
EIC <sub>f</sub>	-0.29*	0.002***	
PEC <sub>f</sub>			
CTG <sub>f</sub>			0.0001***
CFB <sub>f</sub>		-0.0004**	0.00001*
CLP <sub>f</sub>			-0.00002**
EIC <sub>g</sub>		0.002*	-0.00004*
PEC <sub>g</sub>	-0.09**		
CTG <sub>g</sub>			
CFB <sub>g</sub>	-0.09**		0.00001***
CLP <sub>g</sub>	-0.07***		

Hereafter, \*  $\rho < 0.01$ ; \*\*  $\rho < 0.05$ ; \*\*\*  $\rho < 0.1$ ; Total sample size contains 1890 items, and total observations are 126. A blank means that the relation between the independent variable and the dependent variable is insignificant.

**Table 4: Regression Coefficients: Relations among Homogenous Clusters (Low-tech Clusters, H<sub>1</sub>).**

		CTG <sub>f</sub>	CFB <sub>f</sub>	CLP <sub>f</sub>	CTG <sub>g</sub>	CFB <sub>g</sub>	CLP <sub>g</sub>	POPU	GOVI	AW
Dependent Variable	CTG <sub>f</sub>		0.32*	0.42*						0.00002**
	CFB <sub>f</sub>	0.21*							-0.00032***	0.00001**
	CLP <sub>f</sub>	0.51*							0.00042***	-0.00002*
	CTG <sub>g</sub>						0.31*		0.00053***	
	CFB <sub>g</sub>						0.17***	-0.079**		0.00001***
	CLP <sub>g</sub>				0.46*	0.15***				

**Table 5: Regression Coefficients: Relations among Homogenous Clusters (High-tech Clusters, H<sub>1</sub>)**

		EIC <sub>f</sub>	PEC <sub>f</sub>	EIC <sub>g</sub>	PEC <sub>g</sub>	POPU	GOVI	AW
Dependent Variable	EIC <sub>f</sub>		0.32*					
	PEC <sub>f</sub>	0.73*						
	EIC <sub>g</sub>						0.002*	-0.00003*
	PEC <sub>g</sub>					-0.09**		

**Table 6: Regression Coefficients: Relations among Heterogeneous Clusters (How Low-tech Clusters Influence High-tech Clusters, H2a).**

		CTG <sub>f</sub>	CTG <sub>g</sub>	CFB <sub>f</sub>	CFB <sub>g</sub>	CLP <sub>f</sub>	CLP <sub>g</sub>	POPU	GOVI	AW
Dependent Variable	EIC <sub>f</sub>	1.1*		0.35***		0.46*				-0.00002**
	EIC <sub>g</sub>		0.2***				0.37*		0.002*	-0.00004*
	PEC <sub>f</sub>	0.52*				0.25**				
	PEC <sub>g</sub>				0.26**					

**Table 7: Regression Coefficients: Relations among Heterogeneous Clusters (How High-tech Clusters Influence Low-tech Clusters, H2a).**

		EIC <sub>f</sub>	EIC <sub>g</sub>	PEC <sub>f</sub>	PEC <sub>g</sub>	POPU	GOVI	AW	
Dependent Variable	LQ of CTG	CTG <sub>f</sub>	0.27*		0.135**			-0.00036***	0.00001*
		CTG <sub>g</sub>		0.24*		0.14*			
	LQ of CFB	CFB <sub>f</sub>	0.097*					-0.00043**	0.00001*
		CFB <sub>g</sub>				0.15**	-0.083**		0.00002**
	LQ of CLP	CLP <sub>f</sub>	0.21*		0.13***				-0.00001***
		CLP <sub>g</sub>		0.32*			-0.06***	-0.001*	0.00002*

**Table 8: Regression Coefficients: Relations among Heterogeneous Clusters (the Integrated Model, H<sub>2b</sub>).**

	EIC <sub>f</sub>	EIC <sub>g</sub>	PEC <sub>f</sub>	PEC <sub>g</sub>	CTG <sub>f</sub>	CTG <sub>g</sub>	CFB <sub>f</sub>	CFB <sub>g</sub>	CLP <sub>f</sub>	CLP <sub>g</sub>	POPU	GOVI	AW	
Dependent Variable	EIC <sub>f</sub>		0.25**		0.98*		0.34***		0.39*				-0.00002**	
	EIC <sub>g</sub>			-0.147**		0.27**				0.36*		0.002*	-0.00003*	
	PEC <sub>f</sub>	0.17**			0.33**									
	PEC <sub>g</sub>		-0.24**			0.32**		0.25***						
	CTG <sub>f</sub>	0.23*		0.11**					0.158**			-0.0004**	0.00002*	
	CTG <sub>g</sub>		0.15**		0.12**					0.24*				
	CFB <sub>f</sub>	0.07***											-0.0004**	0.00001**
	CFB <sub>g</sub>				0.13**					0.19***	-0.07**			
	CLP <sub>f</sub>	0.16*		0.11***		0.29*		-0.37*						
	CLP <sub>g</sub>		0.25*				0.33*		0.16***				-0.0008**	

**Figures**

Figure 1: Geographical location of Pearl River Delta.



(Cited from Wikipedia, [http://en.wikipedia.org/wiki/Pearl\\_River\\_Delta](http://en.wikipedia.org/wiki/Pearl_River_Delta))