

VARYING SIGNIFICANCE OF INFLUENCING FACTORS IN DEVELOPING HIGH-TECH CLUSTERS

---using cities of The U.S. and China as example

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Abstract

High-tech clusters have become a popular strategy for city development around the world since 1980s. There are many factors that will influence the development of high-tech clusters. Researchers from a range of disciplines have researched to identify specific ingredients for success of high-tech clusters. However, their perspectives are more confined to the theoretical field, but have not solved the problem of the significance of these factors. This thesis tries to answer the following questions: to what extent those factors proposed by researchers influence the development of hi-tech clusters when compared to traditional industry clusters, and compared to different locations. The analysis mainly builds regression models of the influencing factors of high-tech clusters for both U.S. and China. There are also regression models built for traditional industry clusters which played a role as a control group in the research. The result of the regression analysis shows that in the U.S. venture capital is the most important factor in developing high-tech clusters, while in China, the most powerful factors are the academic institutes and government. Some recommendations are also provided to the planners in the U.S. and China at the end of this thesis.

1 Introduction

1.1 Background

Science and technology have developed rapidly since the 1940s. Especially for advanced technologies, such as information technology, biotechnology, new energy technology, industrial clusters have become more and more prevalent. In 1951, Silicon Valley emerged as an industrial cluster that integrated intelligence factors, financial capital and industrial clusters, and achieved unprecedented success. Since the 1980s, high-tech clusters have become a popular strategy for city development around the world. Successful high-tech clusters can attract capital, creating jobs, attracting talent, levying taxes, and increasing the value of land, all of which promote the economic development of a city.

Following Silicon Valley, more than 350 high-tech clusters have been built in the United States, such as the Route 128 high-tech industry zone, North Carolina Research Triangle. In addition, Italy, Spain, the Netherlands, Belgium, Ireland, Sweden, Canada, Australia, Israel and Japan had also established a number of forms of high-tech clusters, as have the former Soviet Union and later Russia, such as the science city of Novosibirsk. Newly emerged economic powers have also created high-tech clusters, such as Zhangjiang-Shanghai in China, Hsinchu-Taipei in Taiwan.

1.2 Research Questions

High tech clusters are the result of several causes. Researchers from a range of disciplines have researched to identify specific ingredients for success. But due to different social systems, cultural traditions, and economic strengths, as well as at multiple stages of development, high-tech clusters in different areas vary in inherent resources, management models, capital resources. Take the United States and China for example: many of the high-tech clusters in the U.S. are the products of a pure market economy, under the typical American "free economy" concept. In contrast, high-tech clusters in China are mostly products of government planning, and government funding comprises a large part of the investment.

This thesis draws upon the issues above and discusses how these factors play similar roles in developing high-tech clusters and conventional industry clusters. It also discusses to what degree local conditions influence the significance of these factors. In other words, this thesis examines to what extent those factors proposed by researchers influence the development of hi-tech clusters when compared to traditional industry clusters, and compared to different locations. The targeted areas chosen in this thesis are the United States and China: these two

countries have large differences in social formation, stages of development, and cultural backgrounds. Furthermore, we need to compare the results of the first questions in order to determine why different factors have different levels of significance. Based on the analysis of the first and second questions, this paper will propose appropriate suggestions for developing high-tech clusters in the U.S. and China.

2 Literature review

2.1 Overview

If we define the starting point of global information technology innovation as the set up of Hewlett-Packard Development Company (HP) in California in 1939, then high technology development dates back more than 70 years; related theories can be traced back more than 100 years. High-tech cluster can be counted as a core part of this innovation and played an important role in the transformation of scientific and technological achievements. Since the 1950s when the first high-tech cluster emerged on the Stanford campus, high-tech clusters have promoted and nurtured high-tech enterprises and entrepreneurs, as well as new technological revolution and new industries.

However, before the 1980s there was little systematic research on high-tech clusters in the academic world and relevant academic papers published. In the early 1980s, Western scholars began to detailed study on the success story of Silicon Valley from different perspectives, including entrepreneurial culture, legal environment, corporate governance, venture capital operation and history. So far, there are two relevant international non-governmental organizations related to high-tech clusters: The first is the International Association of University Research Parks (AURP); the second is the International Association of Science Parks (IASP). Their main functions are to organize research and communication activities related to science and technology clusters, and regularly publish the latest information and research of science and technology parks in different parts of the world.

2.2 Research on the dynamic mechanism of High-tech clusters

Several theories can be applied to the dynamic mechanism of high-tech clusters as followed:

2.2.1 “Innovation” theory

In Joseph Schumpeter’s well-known work *The Theory of Economic Development*, published in 1912, he proposed that innovation should be the critical dimension of economic growth, and defined innovation as entrepreneurs’ selves to implement new combinations of production factors. He pointed out that innovation would spread and cause significant changes in the spatial distribution of industry. High-tech clusters, which are built on the basis of technological innovation, are ruled by this technological innovation theory.

2.2.2 Growth pole theory

The theory of the growth pole appeared in the mid-1950s as an abstract economic concept, and was introduced to the field of regional studies in the 1960s. It was first proposed by the French economist Francois Perroux in 1955. In the field of regional planning, growth pole theory refers to a leading industrial sector surrounded by a groups of joint industries in a region, which demonstrate rapid growth and promote the growth of other sectors through multiplier effects. Since their emergence, high-tech clusters have been playing positive roles as growth poles in the region. High-tech clusters radiate the product, capital, technology, information and even concepts of this area outward, using their powerful force and lead to the spread of high-tech zones in geographic space.

2.2.3 Industrial cluster theory

The representative of The Positioning School Michael Porter believed that “A cluster is a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities.” It is able to gather up related industries and companies to promote products business and the particular industry, thus promote economic development. Industrial clusters help to improve “the opportunities of coordination and cooperation,” because there is a complete supply chain existing in the industrial cluster from the technology to market, and some technologies can be commercialized and translated into real productivity through the industry cluster as soon as possible.^[1] High-tech clusters play a very important role. High-tech clusters can gather all the factors and impetus for innovation together to make innovative industries flourish.

2.2.4 Research on the mode of High-tech clusters

The most famous research on this topic was done by Manuel Castells and Peter Hall from the University of California, Berkeley. In their work, *Technopoles of the world: The Masking of 21st Century Industrial complexes*, published in 1994, they divided the development modes of High-

tech clusters all over the world into four categories: (1) high-tech company industrial complex (2) Science City (3) Technology Park (4) Japan's high-tech city.^[2]

The "high-tech development zone "research group of Chinese Academy of Sciences (1988) has its own method, and concluded five types of development modes of high-tech clusters: incubators, science and technology industrial parks, high-tech industrial zone, the city of science and the city of technology. Xinzhen Wei and Jici Wang al (1993) from Peking University challenged the above modes. They used function to divide the technology zone into three categories: Science Park, city of technology, and high-tech processing zone.

Besides the above research, many methods have been used to analyze the development mode of high-tech clusters. We can get different classifications of development mode from various perspectives, such as development advantage, formation process, and investors,.

Based on Castells and Hall's method, high-tech clusters in the U.S, represented by Silicon Valley, are mainly in the first category, which is based on high-tech companies establishing comprehensive industrial bodies linking R & D and manufacturing. On the other hand Chinese high-tech clusters can be approximated classified in the third category. They are similar to new administrative divisions of industry, and aim to build concentrated high-tech industrial companies in designated areas in order to enhance the survival and development capabilities of the region in international competition and continue to pursue sustained economic growth. From the above classification, it can be seen that this is a government-led model. The influence from the government will become an important factor in the development of the park, or even can be viewed as a crucial factor.

2.2.5 Research on the key factors of successful High-tech clusters

After the success of Silicon Valley, there has been thousands of high-tech clusters created or emerged throughout the world. High-tech clusters are part of the macro economy. Apparently the development of high-tech clusters cannot be realized without growth factors, such as raw materials, labor, capital, technology, knowledge, entrepreneurship and, industrial clustering,. Beside these factors, much research has sought to explain the characteristics of Silicon Valley and other examples of high-tech clusters.

Grabher (1993) proposed that knowledge accumulated system which based on knowledge spillover mechanism are important in the high-tech clusters.

The knowledge accumulated system in high-tech clusters areas makes the cluster to create unique productive knowledge and systematical knowledge, which are converted to shareable knowledge through knowledge spillover mechanism. Therefore the level of accumulation of knowledge in the cluster continues to increase as a whole. Knowledge

accumulation is one of the important determinants of innovation, and the knowledge accumulation level of innovation subject directly affects the level of technological innovation. Therefore, knowledge spillovers increase clusters' levels of knowledge accumulation and enhance technological innovation. At the same time, he developed the innovative theory to the "regional innovation system" level, saying that new regional innovation systems will affect the formation and development of industrial agglomeration, and that the enterprises' innovation cannot be separated from surrounding factors such as management system, customs, laws, and culture. Since the innovation of enterprises has the character of "path dependence" during the innovation process, it must interact with other actors within the region to form the interaction network, and effectively integrated with the systems, and cultural environment, in order to continuously innovate. Besides, Grabher believed that organizations or institutions outside the enterprise such as government, training organizations, universities, etc., have greater capability to improve the regional innovation. ^[3]

When refers to study of spiritual characteristics of the high-tech clusters, Saxenian's work did ground-breaking contribution to this field. Since the early 1980s, her comparative research of the regional advantages of Silicon Valley and Route 128 industrial zone, especially research on regional innovation networks, immigrant culture and entrepreneurial spirit of Silicon Valley has great value for the rest of world in awareness and understanding of Silicon Valley. ^{[4]-[7]} In her work *Regional Advantages: Culture and Competition in Silicon Valley and Route 128*, Saxenian(1994) chose to understand regional economic and industrial systems from the perspective of industrial system and studied these two areas as examples of two industrial system modes. Saxenian got the conclusion that the fundamental reason that why differences between the two modes occur is because they existed in completely different institutional environment and cultural backgrounds. Besides, Saxenian pointed out that an open regional culture of mutual assistance and international industrial cooperation networks is critical to the development of high-tech clusters.

Maillat (1996) asserted that the existence of related industries in industrial clusters provided a convenient professional source of specialization inputs for these enterprises. The existence of such a vendor can enable enterprises to quickly integrate; that is, the geographic concentration of high-tech enterprises make their access to supporting industries and products more convenient. ^[8]

GM. Peter Swann, Martha Prevezer and and David Stout (1998) pointed out that because of the geographical concentration of many factors related to competition in the region, such

as the high-tech enterprises and information of the market, technology accumulates extensively and rapid delivered. This is very important to the enterprises in the competition. ^[9]

Paul Westhead and Stephen Batstone (1998) proposed the importance of location factors of the high-tech clusters through comparison of high-tech enterprises inside and outside high-tech clusters in U.K. They pointed out several key factors that influence the decision of high-tech firms whether to locate in a high-tech cluster are: Overall reputation of the area, parking facilities, convenience of transportation, convenient information exchange and cost. ^[10]

Saxenian. A and Hsu. J. Y (1999) put forward that high-tech clusters consist of many companies and institutions interconnected by technology, information, research, human resources, capital, and other factors through close association industrial correlation. It is easier to form a variety of highly specialized inputs inside the body of concentration. ^[11]

Based on the studies of several large industrial clusters in Africa, McCormick (1999) suggested that knowledge spillovers and technology sharing are the driving force of the high-tech industry in Africa. ^[12]

Samuel Kortum and Josh Lerner (2000) showed with empirical tests that venture capital plays a substantial role in technological innovation. They found that the number of patents generated by \$ 1 in venture capital investment is 3.1 times greater than that of \$ 1 R & D investment in traditional enterprises. ^[13]

Another discussion about this issue is *The Errors: the Economist's Discourse of Silicon Valley Model* edited by Yingyi Qian from University of California, Berkeley. The book combines research on Silicon Valley by several economists such as Saxenian, Masahiko Aoki, Jinglian Wu. The result is an important theory that in the process of developing high-tech industry "the system is more important than technology". ^[14]

In *The Silicon Valley Edge: A Habitat for Innovation and Entrepreneurship*, Silicon Valley's success is boiled down to its environmental conditions which can transform the pioneering spirit into the technological innovation. The authors argue that Silicon Valley's advantage comes from the overall environment, the habitat for innovation and entrepreneurial, and the technological breakthroughs are only results from those spirits. ^[15]

Athreye did detailed study on Cambridge high-tech industrial park, and attributed the appearance of Cambridge high-tech clusters to the good environment of knowledge, abundant human resource, and convenient port conditions of Cambridge Park. ^[16]

Chinese Scholars have also done much research on the key factors of high-tech clusters from the experience of Chinese high-tech clusters.

Xinzhen Wei and Jici Wang (1993) analyzed the significant order of key factors in their book *New Industrial Space*, finding out that intensive intelligence level should be in the first place, followed by the development of technical conditions, talent labors, information network, excellent infrastructure, appropriate basic production and living environment. ^[17]

Kai Yao(1996) believed that the most important factors that affect the location of high-tech industry are: industrial clusters factor, intelligence-intensive areas, the environment and quality of life, and transportation , especially highways and airports. ^[18]

Wen Liang (2003) believes that the impact of the traditional location factors on high-tech clusters is weakening. The major factors in developing high-tech clusters are the intelligence-intensive areas, venture capital-intensive areas, certain technical support conditions, the government's preferential policies, better natural environment and better infrastructure . ^[19]

Yulin Zhao (2004) categorized the factors affecting high-tech clusters into the production factors and the management factors. The production factors include: natural environmental conditions, technical conditions, the quantity and quality of researchers, entrepreneurs, capital factors, the market factors. The management factors include: good transportation and communications infrastructure, a good atmosphere to attract scientists, high-technological innovation system, traditional industries that support the development of high-tech industries and industrial policy of the government. ^[20]

Zheng Wang (2005) proposed that the major influencing factors include: knowledge spillover, intensive human capital, climate and environment, the supply chain environment, transportation conditions and the trade market. ^[21]

Runbang Xie, Guanlin Hu (2006) did research on the relationship between venture capital and high-tech clusters, the phenomenon of concentration of venture capital and the impact of such concentration on high-tech clusters. They proposed that current mechanism of China's venture capital was far from perfect, and Chinese must urgently take steps to improve and perfect the venture capital system to achieve sustainable development of Chinese high-tech clusters, thus creating positive interaction between the between venture capital and high-tech clusters. ^[22]

2.2.6 Summary

It can be seen from the above discussion that former scholars have developed a comprehensive discussion on the high-tech industry cluster, including the key factor of developing high-tech industry cluster, dynamic mechanisms, and relationship with other aspects of the regional economy.

When focus on the key factors field, all the factors proposed by them can be generalized in 5 categories, which are:

- 1) Technique resource, including educational institutions, skilled workers.
- 2) Capital resource, such as venture capital.
- 3) Location factors, such as the geographical condition, climate, supporting facilities.
- 4) Institutional factor, such as knowledge spillovers and technology sharing.
- 5) Spiritual factors.

Some researchers still emphasize the importance of traditional location factors and capital factors, while others believed that the core factors has been changed to technique and institutional factor, such as knowledge spillover environment, and intensive intellectual resources. However, their perspectives are more confined to the theoretical field. Although there are some empirical studies, they mainly discuss measures of the degree of industrial clustering, and apply empirical methods to analyze the effects of each factor on the high-tech industrial agglomeration. Overall, past research mainly discussed the factors influence the high-tech industry cluster theoretically, but has not solve the problem of the significance of these factors.

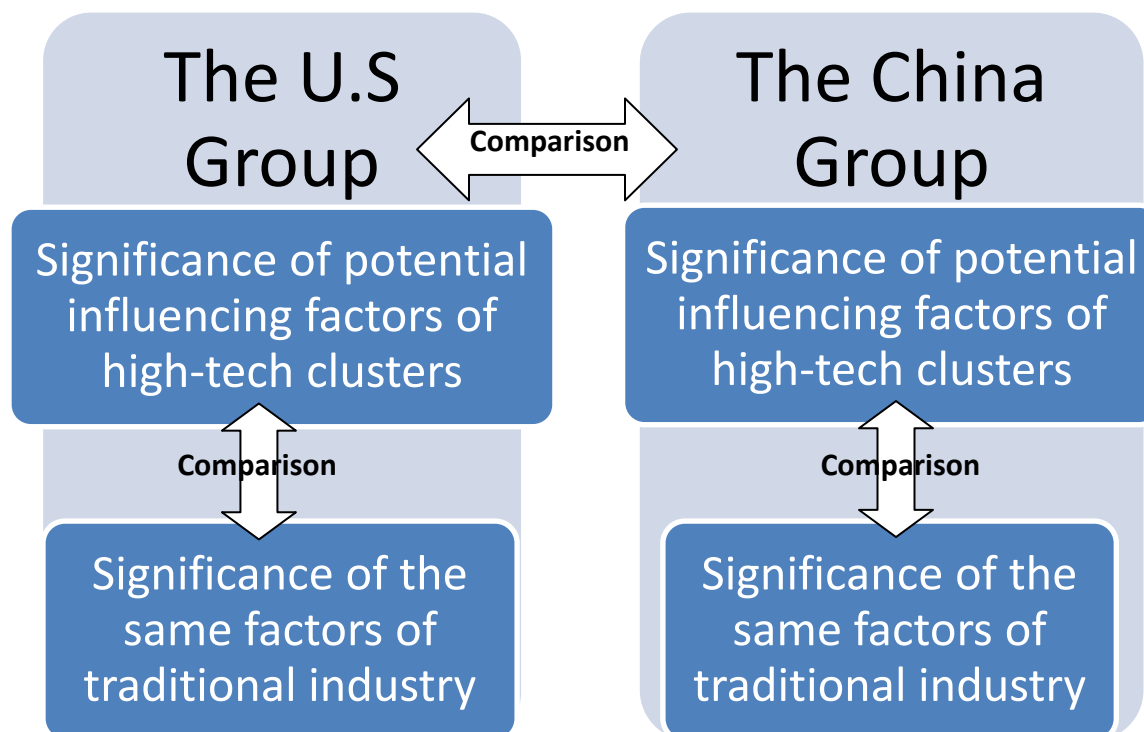
3 Conceptual Framework

3.1 Subject of the study

Based on the aforementioned industry cluster theory and innovation theory, high-tech clusters play an important role in regional development as an innovative system. Therefore, this paper does empirical analysis of significance of potential influencing factors in developing high-tech clusters, which could further help in promoting regional development in both countries.

The method of empirical analysis mainly builds regression models of the influencing factors of high-tech clusters for both U.S. and China. We can examine the influencing factors of high-tech industry cluster from two perspectives. The first is the different influencing factors in high-

tech industry and traditional industry. In other words, do those influencing factors of traditional industry clusters play the same role in high-tech clusters? The traditional part played a role as a control group in the research. The second is the differences of the influencing factors between high-tech clusters in different areas with different background. Therefore we can provide a theoretical basis for developing regional public policies to promote high-tech industry clusters in the U.S. and China.



3.2 Hypothesis

This paper tests several hypotheses:

- 1) The influence of tradition location factors will have less significance for high-tech clusters compared to conventional industry clusters.
- 2) The development of high-tech clusters would have a positive correlation with these indicators, while significant levels of these indicators are different.
- 3) The significance of influencing factors would be different between the U.S. and China.

3.3 Unit of analysis

In the U.S. group, the unit of analysis was MSAs (metropolitan statistical area). There are total 367 MSAs chosen for the analysis. This unit was chosen for two reasons.

- 1) The development of high-tech industry is usually a regional issue which sometimes involves more than one city. The general concept of a metropolitan area is that of a large population nucleus, together with adjacent communities with a high degree of social and economic integration with that core. Metropolitan areas comprise one or more entire counties, except in New England, where cities and towns are the basic geographic units.^[23] Thus metropolitan area is a better unit compared to other unit which are most divided by political reason.
- 2) The Office of Management and Budget (OMB) defines metropolitan areas for purposes of collecting, tabulating, and publishing federal data. Metropolitan area definitions result from applying published standards to Census Bureau data. Since a big part of U.S. data came from U.S. Census Bureau, using MSA as unit could get access to more types of data.

In the China group, specific cities were used as analysis units. These specific cities were picked based on the list of China National High-Tech Industrial Development Zone. China National High-Tech Industrial Development Zones are national level high-tech clusters which were established under the approval of the Chinese State Council. There are currently 87 China National High-Tech Industrial Development Zones. Except Beijing and Shanghai, which have two National High-Tech Industrial Development Zones, the cities selected all have one China National High-Tech Industrial Development Zone. There were total 81 cities chosen after removing some cities which have data missing.

3.4 Defined key concept

3.4.1 High-tech industry

There are many ways to identify high-tech industries. Usually there are two major approaches to take: either the percentage of scientific and technical employment in a particular industry compared to all industries or R&D dollars spent as a percent of total sales, a measure of research intensity.

According to OECD (Organization for Economic Co-Operation and Development), “High-tech” can be classified into following categories.

Industry name	Total R&D-intensity (1999, in %)	International Standard Industrial Classification Code: Revision 3
Pharmaceuticals	10.46	2423
Aircraft & spacecraft	10.29	353

Medical, precision & optical instruments	9.69	33
Radio, television & communication equipment	7.48	32
Office, accounting & computing machinery	7.21	30

3.4.2 Traditional Industry

The conventional concept of traditional industry is an industrial sector that relies heavily on manual labor and craft skills. This sector has existed for centuries. The Types of Traditional Industries always includes but not limited to Agricultural Industries (Farming, Fishery,), Agro processing industries (palm processing industries, fruit processing industries), Mining industries.

3.4.3 Terms used in this paper

The data collected for these two sectors of industry is as close as possible to the defined concepts as mentioned. However due to the level of detail of the data accessible, in some part of the analysis, this paper uses more general categories of these two sectors of industry. These will be clearly stated in the data part of this paper.

3.5 Methods

According to the summary of former research on this topic, the analysis on this topic is always done in qualitative methods such as case study. However the first three categories of influencing factors are quantifiable with some indicators. Using quantitative analysis can make the significance of these factors more intuitional and evaluate the level of significance. For the last two categories, they will be discussed in a preliminary qualitative analysis, and although they cannot be analyzed directly from this research, their importance can be evaluated by the result of other three categories.

The quantitative analysis was done in multiple regression method using SAS software. The dependent variables and independent variables in the U.S. and the China group are showed in the following table. In this table, the variables in different groups with same number are corresponding to each other.

Dependent variables			
The U.S. group	Unit / range of data	The China group	Unit/ range of data

(1) "tech pole" score	0-100	(1) Employment rate of high-tech industry	percentage
(2) Employment rate of traditional industry	percentage	(2) Employment rate of traditional industry	percentage
Independent variables			
The U.S. group	Unit / range of data	The China group	Unit / range of data
(1) R&D expenditures of local colleges and universities	dollar	(1) Number of local colleges and universities	number
(2) High education rate of local labor	percentage	(2) High education rate of local population	percentage
(3) Government support intensity	percentage	(3) Government support intensity	percentage
(4) Funding amount raised by local venture capital	Million dollar	(4) Funding amount managed by local venture capital	10,000 Yuan
(5) Local comfort score	1-5	(5) Local comfort score	1-5
(6) Total population	1 people	(6) Total population	10000 people

- 1) Dependent variable (1) stands for the development level of high-tech industry
- 2) Dependent variable (2) stands for the development level of traditional industry
- 3) Independent variable (1) and (2) are indicators represent technique resource
- 4) Independent variable (3) and (4) are indicators represent capital resource
- 5) Independent variable (5) and (6) are indicators represent location conditions

Thus, the multiple regressions will be done 4 times as followed:

- 1) The first multiple regression involves the dependent variable (1) and each of the indicators in the U.S group
- 2) The second multiple regression involves the dependent variable (2) and each of the indicators in the U.S group
- 3) The third multiple regression involves the dependent variable (1) and each of the indicators in the China group
- 4) The fourth multiple regression involves the dependent variable (2) and each of the indicators in the China group

3.6 Data

Data used in this study was secondary data since the research is at the city or metropolitan area level. Data was gathered mainly from statistic reports released by governments or statistical organizations and later manual arranged unit by unit.

3.6.1 Data for the U.S. group

The data used in U.S group were collected from:

- 1) American Community Survey 2010
Data from American Fact Finder
<http://factfinder.census.gov/home/saff/main.html?lang=en>
- 2) NSF Survey of Research and Development Expenditures at Universities and Colleges 2009
Data from WebCASPAR Integrated Science and Engineering Resources Data System
<https://webcaspar.nsf.gov/index.jsp?expired=expired&js=js>
- 3) North America's High-Tech Economy: The Geography of Knowledge-Based Industries ranks
Data from Milken Institute
<http://www.milkeninstitute.org/pdf/NAHTweb.pdf>
- 4) Local Climatological Data Annual Summary (1971-2000)
Data from National Oceanographic Data Center (NODC)
<http://ols.nndc.noaa.gov/plolstore/plsql/olstore.prodspecific?prodnum=C00095-PUB-A0001#TABLES>
- 5) Interactive Map: the United States of Venture Capital
Data from The Wall Street Journal
<http://blogs.wsj.com/venturecapital/2011/08/04/interactive-map-the-united-states-of-venture-capital/tab/interactive/>
- 6) ZIP Code to County & Metro Equivalence Table
Data from Proximity Decision Making Information
<http://proximityone.com/zipequiv.htm>

3.6.2 Data for the China group

The data used in China group were collected from:

- 1) Annually City Database
Data from Chinese economic statistics database
<http://162.105.138.185:90/scorpio/aspx/main.aspx?width=1014&height=708>

- 2) The second national R&D resource survey
Data from National Bureau of Statistics of China database
<http://www.stats.gov.cn/tjsj/qtsj/d2crd/>
- 3) China Statistical Yearbook 2009
Data from National Bureau of Statistics of China database
<http://www.stats.gov.cn/tjsj/ndsj/2009/indexch.htm>
- 4) China Venture Capital Yearbook 2010
Data from China Yearbook
http://www.chinayearbook.com/yearbook/book_41815.htm
- 5) Monthly climate value of China ground international exchange station dataset (1971-2000)
Data from China Meteorological Data Sharing Service System
http://cdc.cma.gov.cn/shuju/search1.jsp?dsid=SURF_CLI_CHN_MUL_MMON_19712000_CES&tpcat=SURF&type=table&pageid=3

3.7 Validity Threats

In the model estimation, there will be missing variables since there are many factors can influence the industry clusters. In addition, the correlation between independent variables may also affect the final result.

This problem is common in almost all of the quantitative research, and what this paper do to avoid bigger error is to analysis the independent variables one by one with the dependent variable first, and perform the correlation analysis between the independent variables if necessary.

This paper focuses on high-tech industry cluster theory to do some basic, general research on high-tech industrial clustering in the U.S. and China. Limited by the information and structure of knowledge, policy recommendations for promoting the development of high-tech clusters in the U.S. and China require more in-depth study in the future.

Policy recommendations for promoting the development of high-tech clusters in both countries will be based on the analysis result of the quantitative research, and on qualitative analysis of the local conditions of the U.S. and China.

4 Research analysis

4.1 Preliminary Qualitative Analysis

4.1.1 Institutional factor of high-tech clusters in the U.S. and China

In high-tech clusters of the U.S., there are extensive and in-depth contacts and cooperation between governments, social organizations, universities, research institutions and industrial sector. The government's efforts to strengthen cooperation with other parties can provide good public services, government procurement, technology transfer, R & D funding to support industry development. Strict implementation of patent laws has played a significant role in the high-tech industries and the development of the high-tech clusters. A network of innovation cooperation formed between enterprises, R & D department and production personnel. The staff members flow more frequently and is protected by the local laws, and encouraged and tolerated by the regional culture. This process effectively promoted rapid widespread dissemination of information and knowledge in the region, promoting innovation and the formation of productive forces.

In China, local governments are leading development of the high-tech clusters. Local governments continue to explore solutions to the bottlenecks such as the integrated circuit bonded supervision, inspection and quarantine of entry of biomedical materials, land use policy, financing channels and public service platform. However, restrictions like the household registration system, government assessment system are still not yet meet the requirements of the market economy. The free market mechanism is not perfect in China, and the constructions of social credit and intellectual property still have a long way to go. Therefore, there is a lack of trust between the relevant subjects in high-tech clusters, and deep-seated, open cooperation is difficult to achieve.

4.1.2 Spiritual factor of high-tech clusters in the U.S. and China

Take Silicon Valley as the example of the U.S., as Saxenian and other scholars have pointed out, the people who work in Silicon Valley consider innovation and entrepreneurship fun. People there are encouraged to try, compete, and tolerate failure. People are interested in mutual exchange, learning and cooperation. In addition, the collision and fusion of different races and cultures are very useful in generating innovation. Immigrants, especially senior personnel, can contact their place of birth to help Silicon Valley to build a global industry networks, and gain the integration advantages of the global resources.

In China, use Shanghai-Zhangjiang as example, although the managers of the high-tech park tried to hold many cultural and sports brand activities and strive to create similar culture as Silicon Valley, but it is still with limited success in nurturing innovative entrepreneurial culture. This may mainly due to the following reasons: traditional Chinese culture such as moderation, "valuing official titles", and the Shanghai local tradition to seek high salaries and the white-collar culture, still deeply influence the people of the high-tech park.

4.2 Quantitative Variable Calculation and Selection

4.2.1 Dependent variables in the U.S. group

The variable (1) showing the development level of high-tech clusters is the "tech pole" score. The score value came from a report made by the Milken Institute. They used the latest available 2007 data for U.S. and Canadian metros in their analysis. In the report, North America's High-Tech Economy: The Geography of Knowledge-Based Industries ranks, the researchers of Milken Institute examined the locations and patterns of growth in nineteen high-tech industry categories. They then aggregated those results to determine overall high-tech performance. This benchmarking metric is based on employment and wages; it also looks at the concentration of technology in the local economy and each metro's relative share of aggregate North American activity.^[24]

- 1) Pharmaceutical and Medicine Manufacturing: NAICS 3524
- 2) Commercial and Service Industry Machinery Manufacturing: NAICS 3333
- 3) Computer and Peripheral Equipment Manufacturing: NAICS 3341
- 4) Communications Equipment Manufacturing: NAICS 3342
- 5) Audio and Video Equipment Manufacturing: NAICS 3343
- 6) Semiconductor and Other Electronic Component Manufacturing: NAICS 3344
- 7) Navigational, Measuring, Electro-medical, and Control Instruments Manufacturing: NAICS 3345
- 8) Manufacturing and Reproducing Magnetic and Optical Media: NAICS 3346
- 9) Aerospace and Products and Parts Manufacturing: NAICS 3364
- 10) Medical Equipment and Supplies Manufacturing: NAICS 3391
- 11) Software Publishers: NAICS 5112
- 12) Motion Picture and Video Industries: NAICS 5121
- 13) Telecommunications: NAICS 517
- 14) Data Processing, Hosting, and Related Services: NAICS 518
- 15) Other Information Services: NAICS 5191
- 16) Architectural, Engineering, and Related Services: NAICS 5413

- 17) Computer Systems Design and Related Services: NAICS 5415
- 18) Scientific Research and Development Services: NAICS 5417
- 19) Medical and Diagnostic Labs: NAICS 6215

On the MSA level, the employment data at NAICS code level is not available and the data available is only at level of 14 larger categories of industry. Thus the variable (2) showing the traditional industry development level in the U.S. group is the total employment rate of following industry categories in each MSA and Year of data is 2010:

- 1) Agriculture, forestry, fishing and hunting, and mining
- 2) Construction
- 3) Manufacturing
- 4) Wholesale trade
- 5) Retail trade
- 6) Transportation and warehousing, and utilities

4.2.2 Dependent variables in the China group

In the China group, there is no similar research calculating the “tech pole” score for the cities, thus the variables showing the development level of both high-tech and traditional industry are also the employment rate of specific industry categories in 2009. Limited by the level of detail of the data, which was only divided in 19 industry categories, the high-tech industry categories are:

- 1) Professional, scientific, and management service
- 2) Information related industry and service

And the traditional industry categories are:

- 1) Agriculture, forestry, fishing and hunting
- 2) Mining
- 3) Manufacturing
- 4) Construction
- 5) Wholesale trade and retail trade
- 6) Transportation and warehousing, and utilities

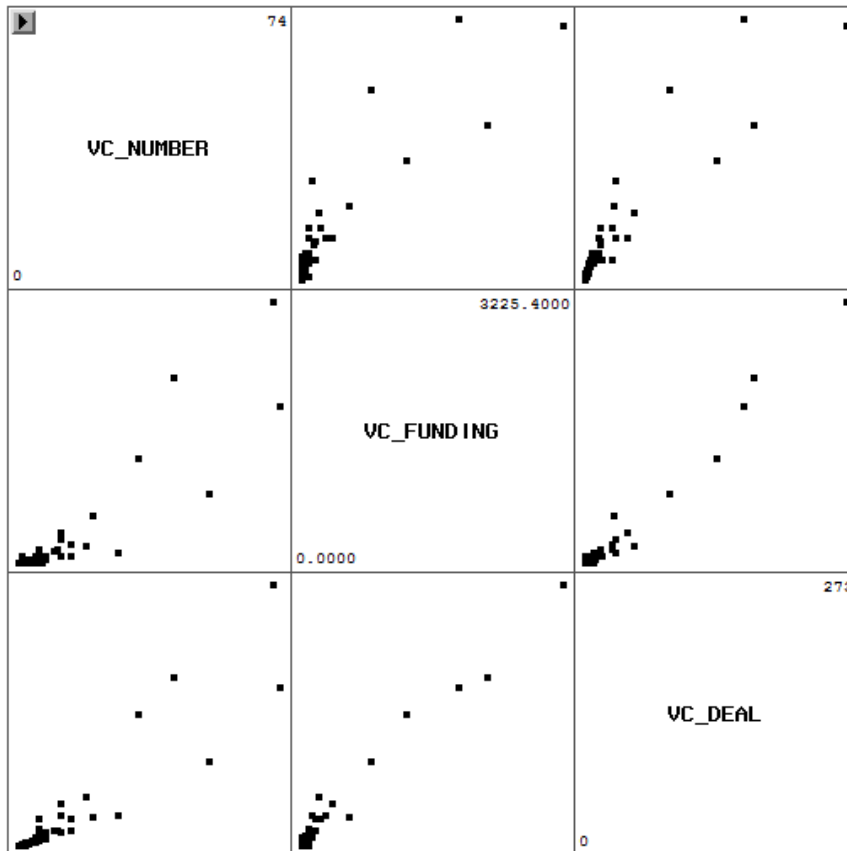
4.2.3 Independent variables in the U.S. group

For Independent variable (1) and (2), which show the technique resource, more than 2 variables were collected and calculated, including: the number of local colleges and universities (2009), R&D expenditures of local colleges and universities (2009), high-educated people rate of the whole population (2010), high-educated people rate of the labor source (2010). High-educated people refer to people who have a college degree of higher degree.

Since the first two variables and the last two variables have obvious correlation, R&D expenditures of local colleges and universities (2009) and educated rate of the labor source (2010) were chosen to be independent variables since they are more related to high-tech industry.

Independent variable (3) intensity of government support was calculated by following equations using 2009 data: Intensity of government support= (Federal provided academic R&D expenditure + State or Local Government provided academic R&D expenditure)/ Total academic R&D expenditure of the local colleges and universities.

For Independent variable which shows the venture capital related factors, there were 3 variables collected and calculated for chosen including using 2011 data: the amount of local venture capital, funding amount raised by venture capital, total deals of venture capital in the targeted area. Using interactive analyze function of SAS to do the cross-analysis of these three variables, the result is as follows:



The cross-analysis scatter chart showed that these three variables have very strong correlation to each other. Then only one of them was needed in the final analysis. The funding amount raised by venture capital (2011) was chosen as independent variable (4) because of its greater data value range.

Independent variable (5) Local comfort score is reclassified by human comfort index. Human comfort index is biometeorology indicators developed based on the heat exchange between the human and atmospheric environment. The human comfort index reflects the feelings of the body of air temperature, humidity and other factors, and these factors were “comfortable” digitized and graded^{[25]-[27]}. Considering the influence of temperature and humidity on human comfort, this paper chose the most widely used formula to calculate the human comfort index $I_{HC} = T - (0.55 - H_R) \times (T - 58)$.^[28] In this formula, I_{HC} stands for human comfort index, T stands for temperature in °F unit, and H_R stands for humidity in percentage. Data used for temperature and humidity was the annual average data from 1971-2000.

When the index is between 59-70, the human body will feel very comfortable. At higher index, the body feels hotter and less comfortable. At lower index, the body feels colder and less comfortable. Thus the comfort score was reclassified based on the comfort index value of each analysis unit as following table:

Human Comfort Index	86-88	80-85	76-79	71-75	59-70	51-58	39-50	26-38	≤25
Local Comfort Score	1	2	3	4	5	4	3	2	1

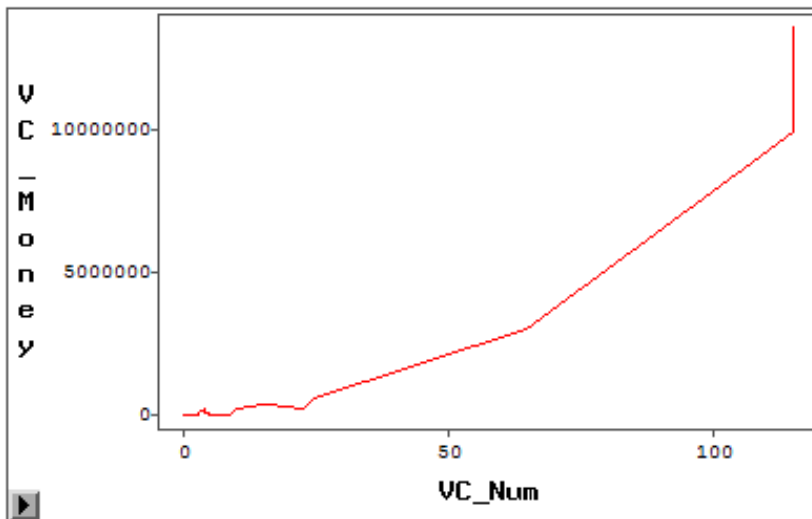
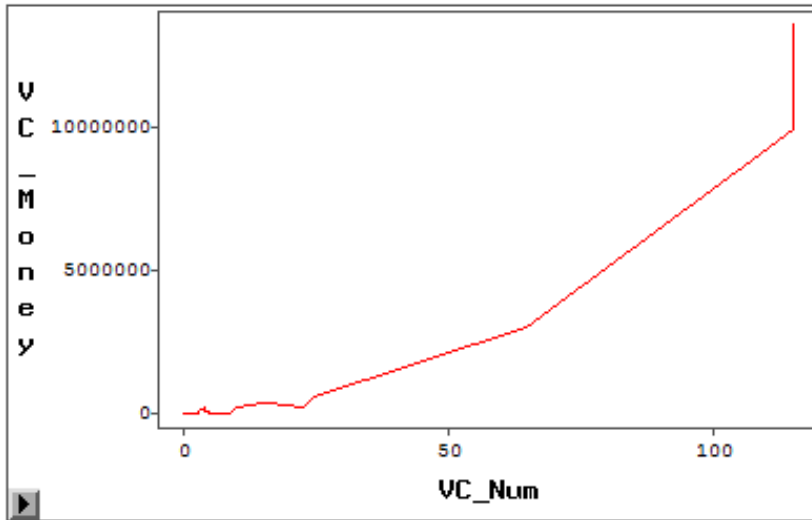
The last independent variable (6) also reflects the location condition. Total population (2010) was chosen to show the size of the target area.

4.2.4 Independent variables in the China group

For Independent variable (1) and (2), which show technical resources in China, data is accessible only on the number of local colleges and universities (2009) and high education rate of the whole population (2009). Besides, the high-educated people rate of the population is only accessible at province level. Thus the same high education rate of the whole population was used for several different cities in the same cities.

Independent variable (3), intensity of government support, was calculated by the following equations: Intensity of government support= Government provided R&D expenditure / Total R&D expenditure of the area. Year of data is 2009. This data is also available at province level.

For the Independent variable, which shows the venture capital related factors, there were two variables collected and calculated using 2009 data including: the amount of local venture capital, funding amount managed by venture capital in the targeted area. Using interactive analyze function of SAS to do the correlation analysis of these two variables, the result is as follows:



There is also a strong correlation between these two variables in the China part. Thus Funding amount managed by venture capital (2009) was chosen as independent variable (4) because of its greater data value range.

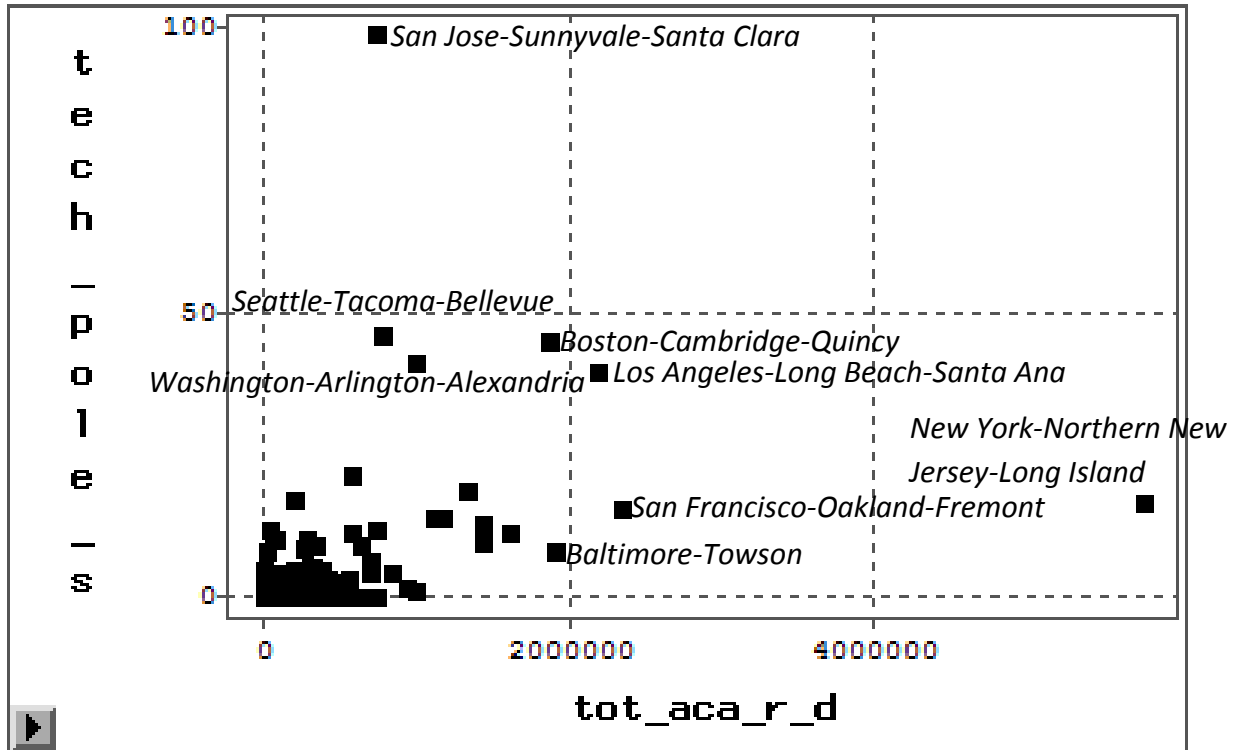
For Independent variable (5) Local comfort score in the China group, the calculation and reclassification is the same as the U.S. Group, and has the same year of data.

For Independent variable (6), total population, the year of data is 2009.

4.3 Linear regression analysis

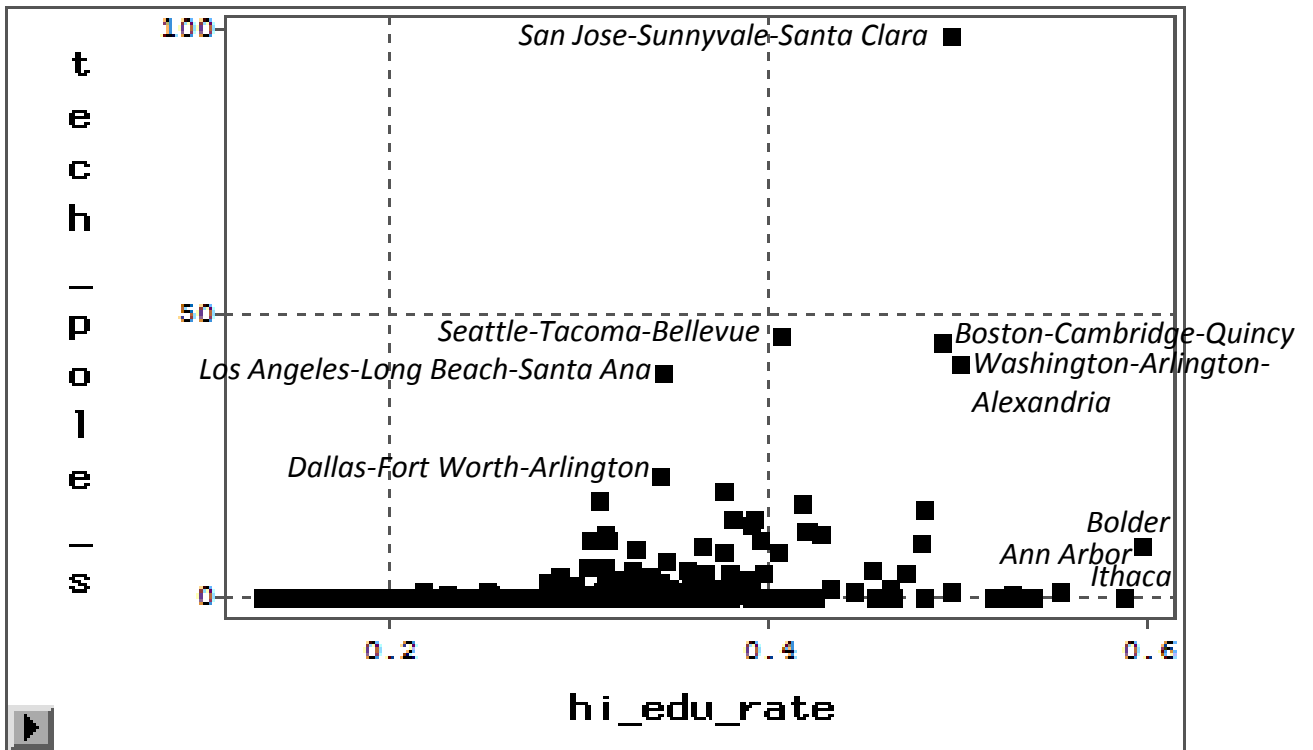
4.3.1 The U.S. group

4.3.1.1 Linear regression of dependent variable (1) tech pole score and Independent variable (1) total academic R&D expenditure of local colleges and universities



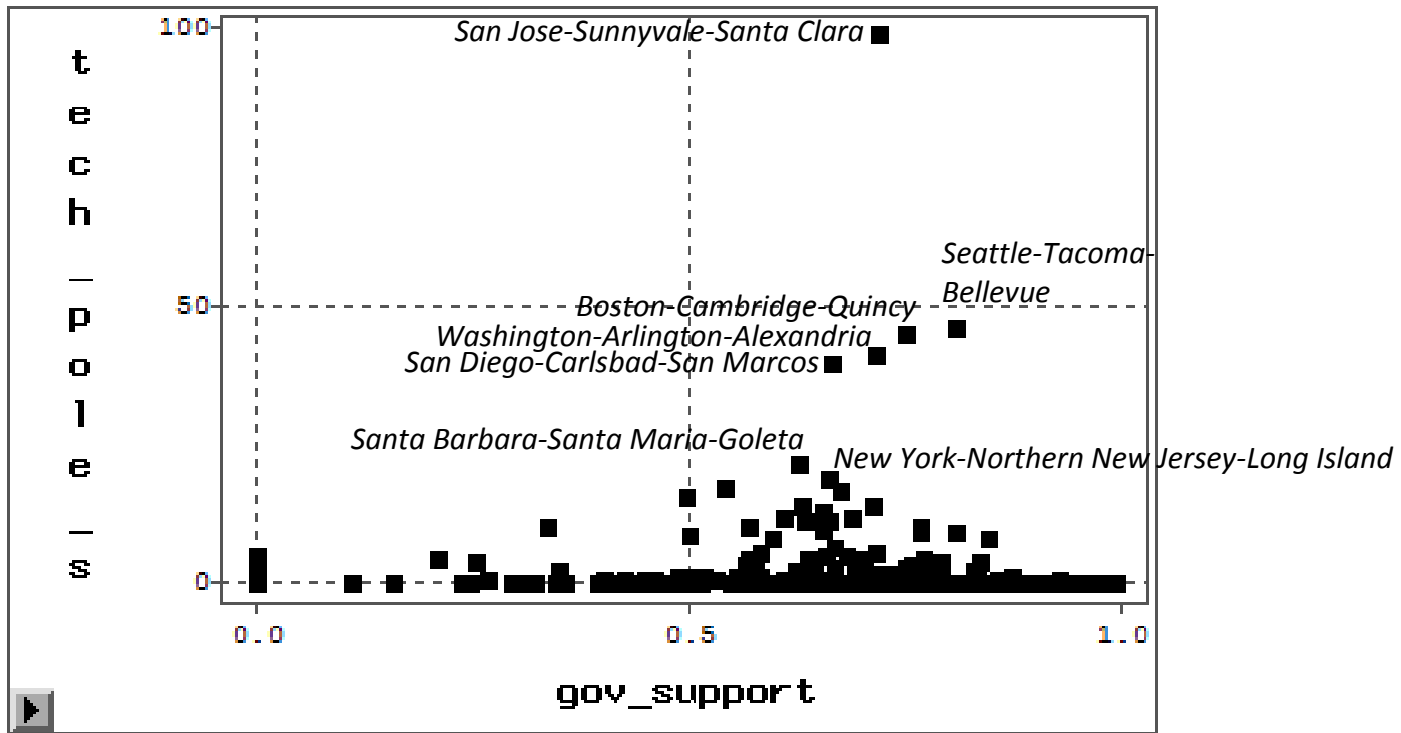
From the scatter chart we can tell there seems to be a relation between the tech pole score and total academic R&D expenditure of local colleges and universities for most of the MSAs. There are several exceptions, such as the rank 1 high-tech area San Jose-Sunnyvale-Santa Clara Metro Area, which has a relatively medium academic R&D expenditure. And the total \$5.8 million annually academic R&D expenditure of the New York-Northern New Jersey-Long Island Metro Area, which is more than twice of the second MSA in this field, does not make this area have better performance on high-tech clusters.

4.3.1.2 Linear regression of dependent variable (1) tech pole score and Independent variable (2) High education rate of labor



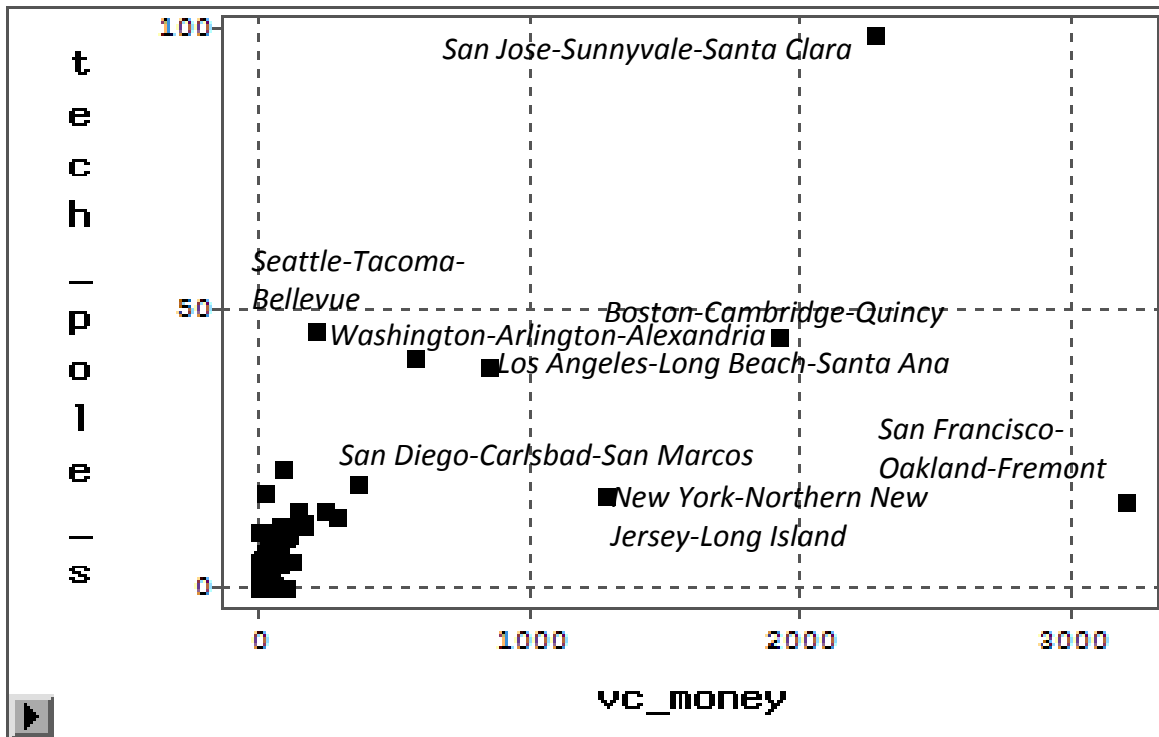
It can be observed that as the tech pole score rising, the correlation between the two factors is more obvious. However, those MSAs have a low tech pole score, which formed a big part of the data pool, the high education rate varies in a large range and did not show a significant relation.

4.3.1.3 Linear regression of dependent variable (1) tech pole score and Independent variable (3) government support intensity



On government support field, for several top MSAs with relatively high tech pole score, the government support seems to play more important role when compared to the rest, however the top MSA is a very small part of the data pool. Thus no obvious trend can be identified from this chart.

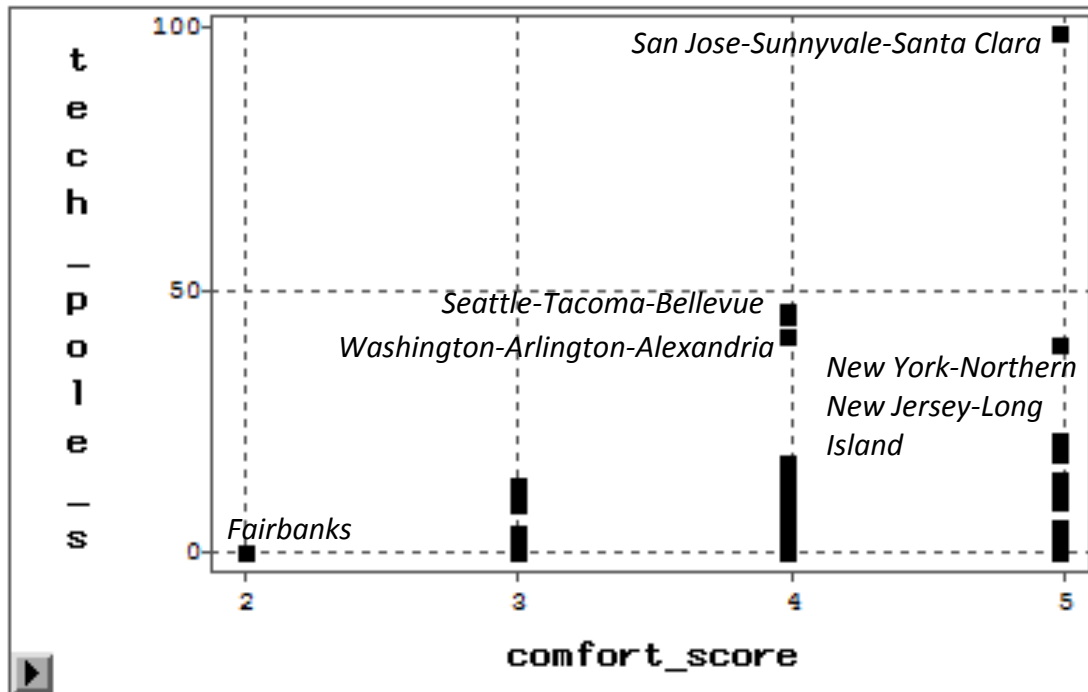
4.3.1.4 Linear regression of dependent variable (1) tech pole score and Independent variable (4) funding raised by venture capital



General speaking, the funding raised by venture capital has an obvious positive relationship with the tech pole score as the chart showed. However for the MSAs with relatively high venture capital funding, the situation is not the same. The MSA with most venture capital funding is San Francisco-Oakland-Fremont Metro Area with \$3.2 billion, which is ranked 10 in the North America. However the rank 1 area San Jose-Sunnyvale-Santa Clara Metro Area had only \$2.3 billion, only 2/3 of the level enjoyed in San Francisco-Oakland-Fremont.

Those exceptions may be explained because many of the relatively high score MSAs are in the Pacific region (5 out of top 10). Thus venture capital companies in this region provide their services not only to the MSA the company located, but also the whole region.

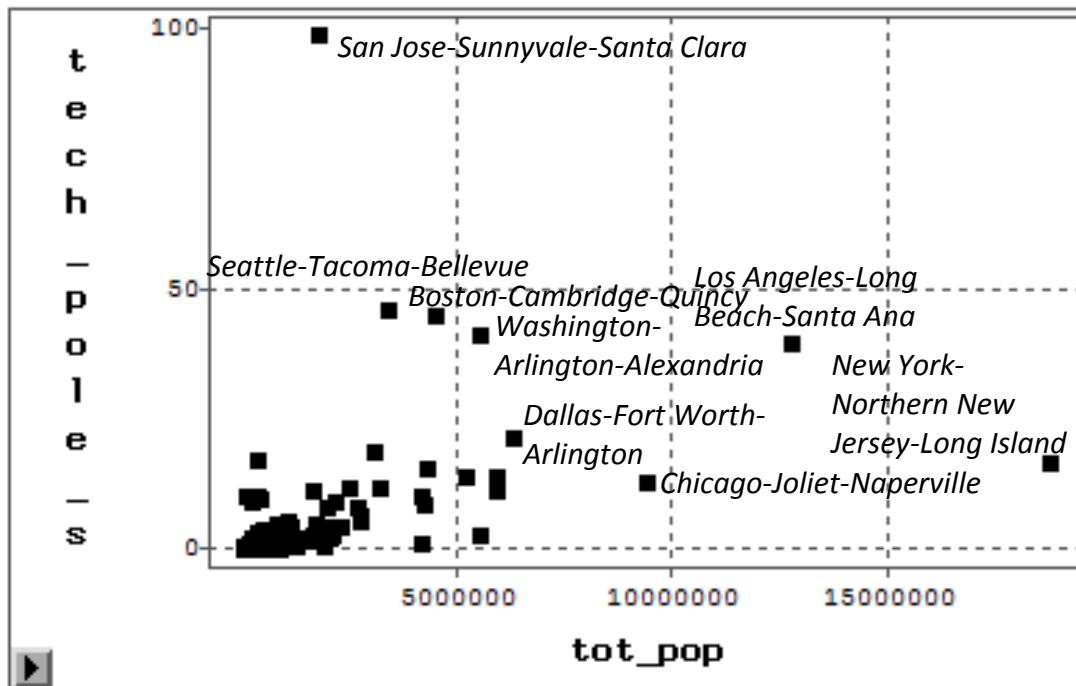
4.3.1.5 Linear regression of dependent variable (1) tech pole score and Independent variable (5) human comfort score



Generally speaking, the ladder-like chart showed a positive relationship between the tech pole score and comfort score. It can be clearly seen in the chart that a large percentage of MSAs with comfort score of 4 or 5 have higher tech pole score when compared to MSAs with low comfort score.

Still, the exception happened among top high-tech MSAs. The second top high-tech MSA, Seattle-Tacoma-Bellevue, and the third MSA, Washington-Arlington-Alexandria, each have a comfort score of 4, which is not in the highest comfort score group.

4.3.1.6 Linear regression of dependent variable (1) tech pole score and Independent variable (6) total population



In this chart, a positive trend showed clearly in the group of MSAs which has a population no more than 10 million.

The San Jose-Sunnyvale-Santa Clara area is the location of Silicon Valley, and it can be explained that it has a relatively low corresponding population because of the high technology density there. Once again, New York-Northern New Jersey-Long Island, which has the largest population of any U.S. MSA, became a strange point on the chart with worse performance than expected.

4.3.1.7 Multiple regression for dependent variable (1)

The first attempt at building a multiple regression model for the U.S. group had the following result:

The REG Procedure
Model: MODEL1

Dependent Variable: Tech Pole Score

Number of Observations Read	366
Number of Observations Used	353
Number of Observations with Missing Values	13

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	11745	1957.45089	80.16	<.0001
Error	346	8449.26082	24.41983		
Corrected Total	352	20194			

Root MSE	4.94164	R-Square	0.5816
Dependent Mean	2.10822	Adj R-Sq	0.5743
Coeff Var	234.39932		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	-8.78457	2.04547	-4.29	<.0001	0
Total Academic R&D	1	-0.00000654	0.00000122	-5.36	<.0001	-0.38503
High education rate	1	21.54899	4.13510	5.21	<.0001	0.24470
Government Support	1	-0.19567	0.89653	-0.22	0.8274	-0.00899
Money raised by VC	1	0.01921	0.00132	14.61	<.0001	0.63603
Comfort Score	1	0.80912	0.35455	2.28	0.0231	0.08334
Total Population	1	0.00000215	2.943715E-7	7.30	<.0001	0.45620

The result showed that the model was successfully built. The R-square value of this model is 0.5816, which means that 58.16% of the dependent variables can be explained by this model.

Given that this research has a strong sociology background, this is a relatively high R-square value. Besides, 5 out of 6 independent variables were significant to the model according to the t value and $Pr > |t|$.

The higher of the $|t|$ value, the higher the significance of the independent variable. Usually, an independent variable with a $|t|$ value larger than 2 will be considered significant. In this model, 5 independent variables are significant. The standardized estimate value in the model showed the relative importance of the effects of independent variables not affected by the measurement scale. Therefore, there are 5 significant variables, listed here from highest to lowest importance:

- 1) **Funding raised by local venture capital**
- 2) **Total population**
- 3) **Total academic R&D expenditures of local colleges and universities**
- 4) **High education rate of labor**
- 5) **Human comfort score.**

It is also must be pointed out that the top 4 significant independent variables all have probabilities higher than 99.99% to successfully explain the dependent variable. This is because they all have a $Pr > |t|$ smaller than 0.0001.

The model generated an unexpected result: the relationship between total academic R&D expenditure of local colleges and universities and the tech pole score is negative, not positive as the hypothesis

Following the model selection rules, after removing the insignificant variable from the first model, the second multiple regressions is like this:

The REG Procedure
Model: MODEL2
Dependent Variable: Tech Pole Score

Number of Observations Read	366
Number of Observations Used	353
Number of Observations with Missing Values	13

Analysis of Variance

Sum of	Mean
--------	------

Source	DF	Squares	Square	F Value	Pr > F
Model	5	11744	2348.70843	96.45	<.0001
Error	347	8450.42403	24.35281		
Corrected Total	352	20194			
Root MSE		4.93486	R-Square 0.5815		
Dependent Mean		2.10822	Adj R-Sq 0.5755		
Coeff Var		234.07744			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	-8.70821	2.01256	-4.33	<.0001	0
Total Academic R&D	1	-0.00000652	0.00000122	-5.36	<.0001	-0.38397
High education rate	1	21.10744	3.60143	5.86	<.0001	0.23969
Money raised by VC	1	0.01924	0.00133	14.69	<.0001	0.63676
Comfort Score	1	0.80236	0.35271	2.27	0.0231	0.08264
Total Population	1	0.00000214	2.916377E-7	7.34	<.0001	0.45448

Compare the modified model to the first one, the R-square value is 0.5815, almost the same as the former 0.5816, which means removing the government support factors from the first model almost have no effect on the explanation ability of the other 5 independent variables. What's more, except the human comfort score, the rest 4 high significant variables all had a standardized estimated value.

Therefore, the final equation between the tech pole score and the independent variables is:

Tech pole score = - 8.70821 - 0.00000652 (total academic R&D expenditure of local colleges and universities) + 21.10744 (High education rate of labor) + 0.01924 (total money amount in million dollar raised by local venture capital) + 0.80236 (human comfort score) + 0.00000214(total population)

4.3.1.8 Multiple regression for dependent variable (2)

The result of multiple regression of control group of traditional industry is as followed:

The REG Procedure
Model: MODEL3
Dependent Variable: Traditional Industry Employment Rate

Number of Observations Read	366
Number of Observations Used	347
Number of Observations with Missing Values	19

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	0.62831	0.10472	48.92	<.000
Error	340	0.72787	0.00214		
Corrected Total	346	1.35618			

Root MSE	0.04627	R-Square	0.4633
Dependent Mean	0.39126	Adj R-Sq	0.4538
Coeff Var	11.82559		

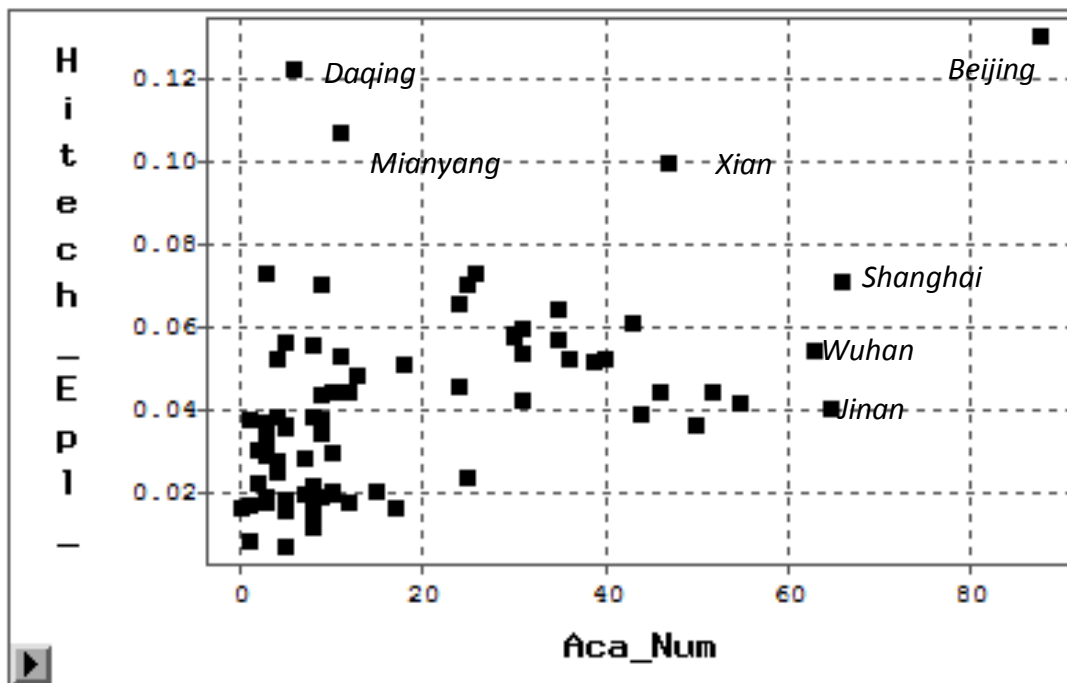
Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	0.60273	0.01919	31.41	<.0001	0
Total Academic R&D	1	-1.46138E-8	1.143672E-8	-1.28	0.2022	-0.10484
High education rate	1	-0.4687	0.03884	-12.07	<.0001	-0.64444
Government Support	1	-0.01633	0.00847	-1.93	0.0547	-0.09034
Money raised by VC	1	0.00002409	0.00001232	1.96	0.0512	0.09731
Comfort Score	1	-0.01607	0.00333	-4.82	<.0001	-0.20085
Total Population	1	2.665631E-9	2.757811E-9	0.97	0.3344	0.0689

The result shows there are 2 independent variables: high educated employment rates and human comfort scores are also significant with traditional industry. However, the relationship between these two independent variables and the dependent variable is reverse. These two variables have a negative relationship with the traditional industry employment rates.

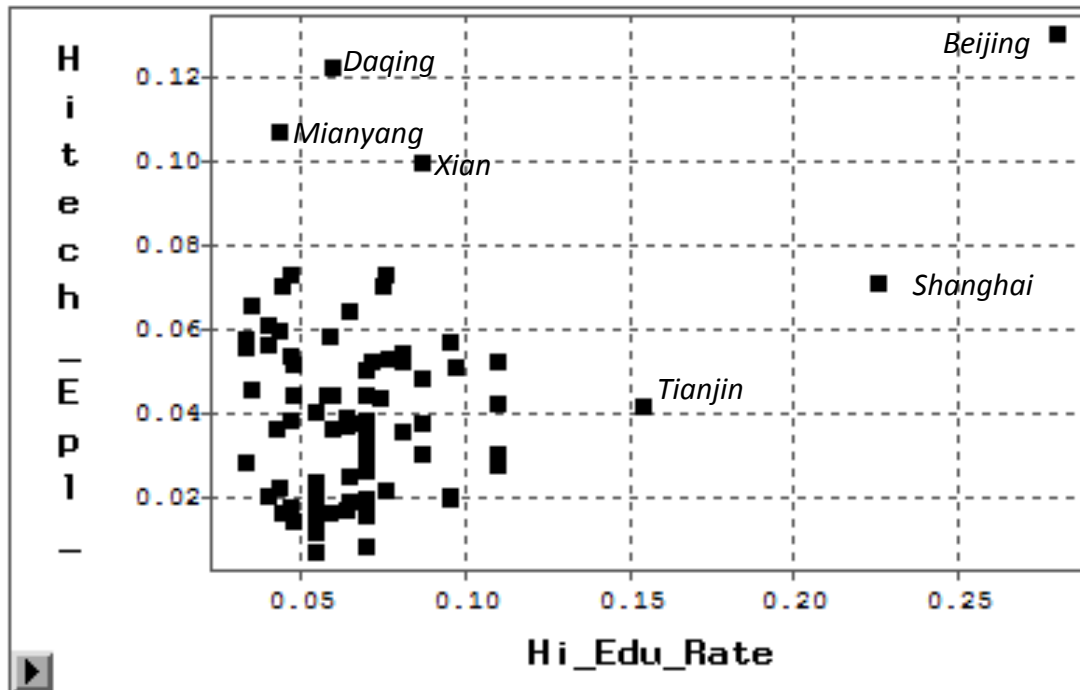
4.3.2 The China group

4.3.2.1 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (1) number of local colleges and universities



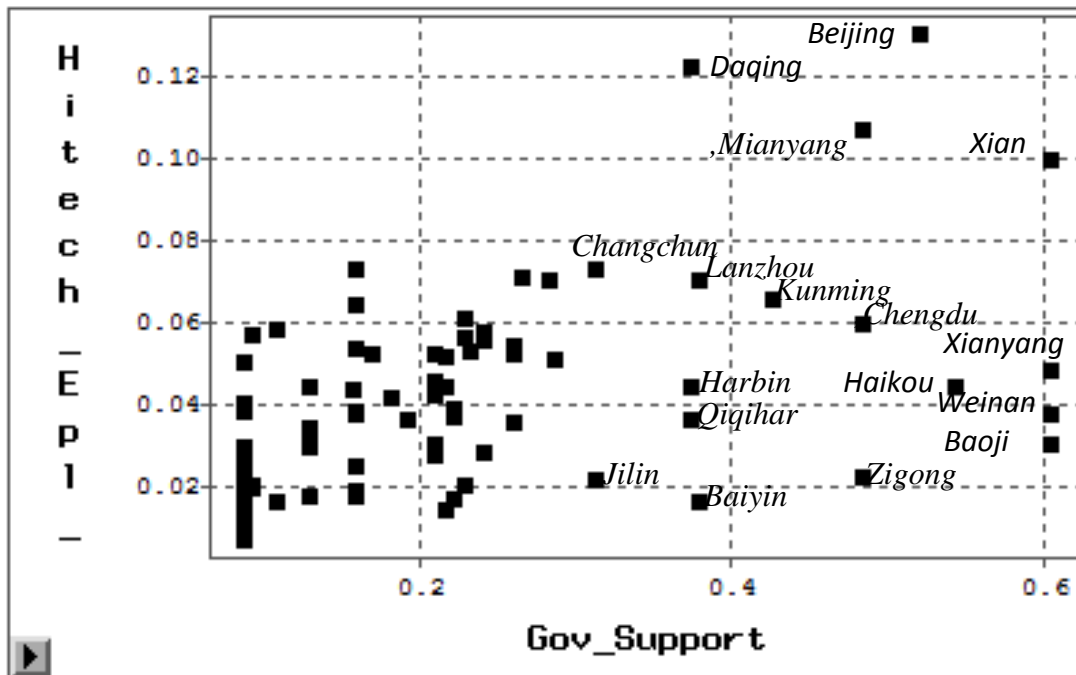
The relation between the number of colleges and universities showed a positive relationship with the high-tech industry employment rate.

4.3.2.2 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (2) high education rate of the whole population



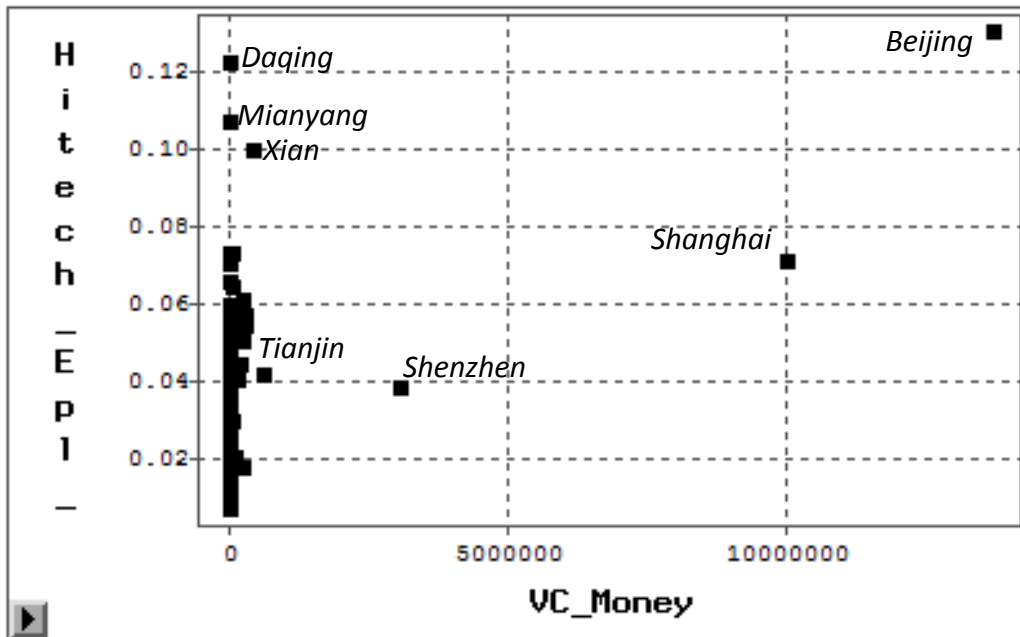
The three cities with highest high education rate show an increasing trend in the right part of the chart. However, most of the rest cities seem scattered randomly in the area between 5%-12% high education rate area, thus no obvious trend can be told from this chart.

4.3.2.3 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (3) government support intensity



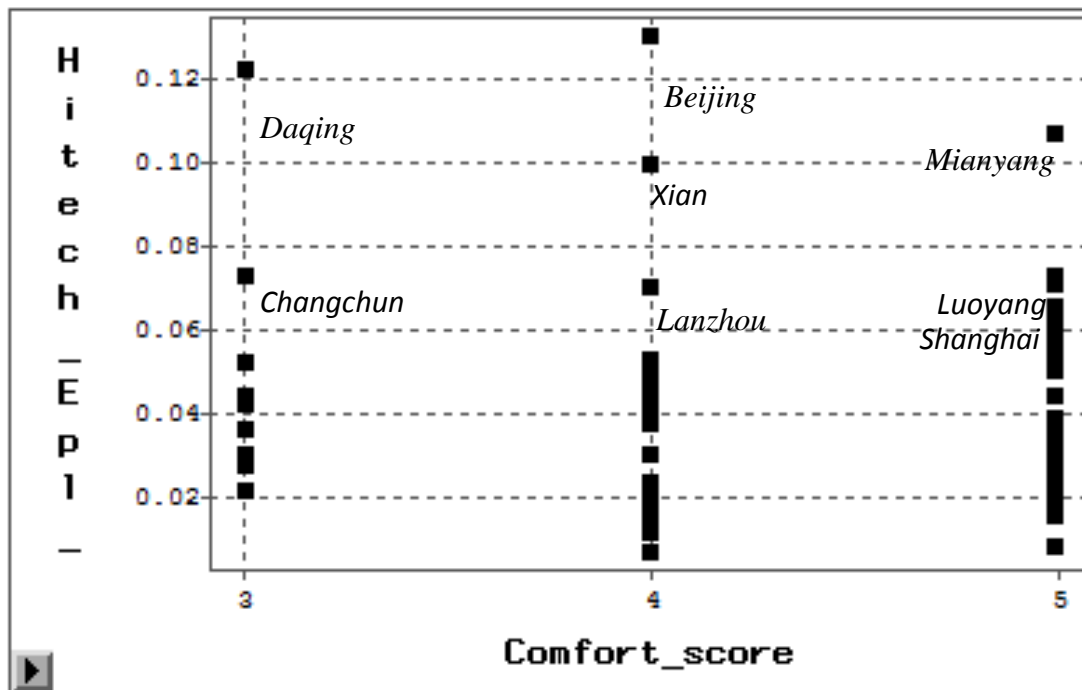
Generally speaking, a positive relationship exists between the intensity of government support and resulting high-tech industry employment rate. It is noticeable that intensity of government support is strongest for Xian, Xianyang, Weinan and Baoji. However, only Xian's performance matched its higher high-tech employment rate. This is because the data for intensity of government support is at province level, and the three other cities are in the same province of Xian. It is possible that much of the government's support flowed to Xian because it is the capital of the province.

4.3.2.4 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (4) funding managed by local venture capital



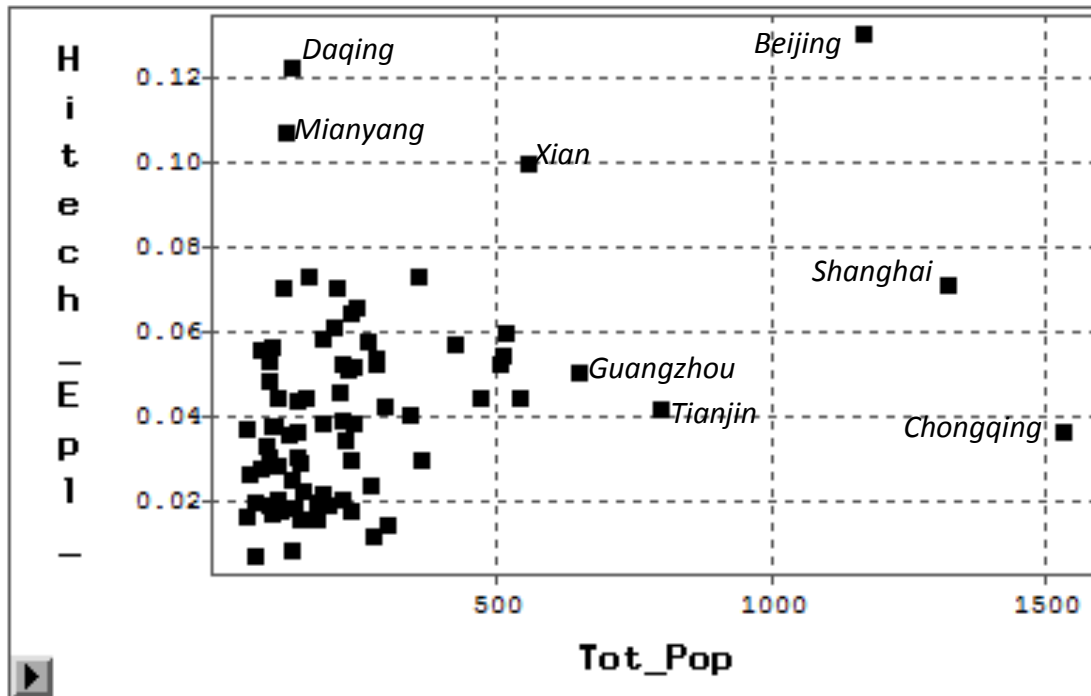
Most of the points are concentrated along or near the 0 axis of VC_Money. This is because half of the cities do not have venture capital, and in those which have venture capital, most of them have very few number of venture capital no more than 5. It is clear that most funding managed by venture capital in China is concentrated in Beijing, Shanghai and Shenzhen, and as this funding continues to rise, high-tech employment is also climbing.

4.3.2.5 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (5) human comfort index



There is no any trend can be found in this chart. The performance of different cities seems to have no correlation with the human comfort score.

4.3.2.6 Linear regression of dependent variable (1) High-tech industry employment rate and Independent variable (6) total population



The chart can be divided into two parts: those cities with population less than 5 million and those cities with population more than 5 million (The unit of the population is 10,000 people). However, it only shows the percentage of cities with relative large population, but no trend showed a clear relationship between population size and high-tech employment.

4.3.2.7 Multiple regression for dependent variable (1)

The first attempt of multiple regressions has the following result:

The REG Procedure
Model: MODEL4
Dependent Variable: High-tech Industry Employment Rate

Number of Observations Read	81
Number of Observations Used	80
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	0.02329	0.00388	11.91	<.0001
Error	73	0.02380	0.00032597		
Corrected Total	79	0.04708			
Root MSE		0.01805	R-Square	0.4946	
Dependent Mean		0.04202	Adj R-Sq	0.4531	
Coeff Var		42.96564			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	0.02847	0.01900	1.50	0.1384	0
Total Academic institutions	1	0.00063471	0.00016766	3.79	0.0003	0.49526
High education rate	1	-0.09915	0.10151	-0.98	0.3320	-0.15031
Government Support	1	0.07071	0.01498	4.72	<.0001	0.41843
Money managed by VC	1	4.161815E-9	2.04656E-9	2.03	0.0456	0.32655
Comfort Score	1	-0.0009263	0.00318	-0.29	0.7717	-0.02746
Total Population	1	-0.00001765	0.00001333	-1.32	0.1896	-0.18829

The R-square value of this model is 0.4946, which means that 49.46% of the dependent variables can be explained by this model. Since this research has a strong sociology background, this is also a relatively high R-square value.

Known from the t value and Pr > |t|, there were only 3 independent variables chosen as significant in this model. They are as followed from higher significance to lower significance:

- 1) Number of local colleges and universities**
- 2) Intensity of government support**
- 3) Money managed by local venture capital**

Following the model selection rules, after removing the insignificant variable from the first model, the second multiple regression is as followed:

The REG Procedure
Model: MODELS
Dependent Variable: High-tech Industry Employment Rate

Number of Observations Read	81
Number of Observations Used	80
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	0.02231	0.00744	22.82	<.0001
Error	76	0.02477	0.00032592		
Corrected Total	79	0.04708			

Root MSE	0.01805	R-Square	0.4739
Dependent Mean	0.04202	Adj R-Sq	0.4532
Coeff Var	42.96186		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	0.01610	0.00422	3.81	0.0003	0
Total Academic institutions	1	0.00047854	0.00012503	3.83	0.0003	0.37340
Government Support	1	0.07272	0.01433	5.08	<.0001	0.43033
Money managed by VC	1	1.912009E-9	1.253211E-9	1.53	0.1312	0.15002

In the new model, the number of colleges and universities and intensity of government support were still significant, but the funding managed by local venture capital had a new t value of less than 2. This is possible because the former t value is only 2.03, which is very close to 2, meaning

the significant level of this variable has quite a low significance, and would be easily influenced by any modification to the model.

Following the model selection rules once again, the funding managed by local venture capital was removed from the second model, and the last multiple regression is as followed:

The REG Procedure
Model: MODEL6
Dependent Variable: High-tech Industry Employment Rate

Number of Observations Read	81
Number of Observations Used	80
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.02156	0.01078	32.51	<.0001
Error	77	0.02553	0.00033154		
Corrected Total	79	0.04708			
Root MSE	0.01821	R-Square	0.4578		
Dependent Mean	0.04202	Adj R-Sq	0.4437		
Coeff Var	43.33068				

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	0.01441	0.00411	3.51	0.0008	0
Total Academic institutions	1	0.00057552	0.00012503	5.30	<.0001	0.44907
Government Support	1	0.07272	0.01433	5.28	<.0001	0.44772

For these two independent variables, their standardized estimate values are almost the same.

Therefore, the final equation between the high-tech industry employment rate and the independent variables is:

High-tech industry employment rate= 0.01441+0.00057552(number of local colleges and universities) + 0.07272(government support rate)

4.3.2.8 Multiple regression for dependent variable (2)

The result of multiple regression of control group of traditional industry is as followed:

The REG Procedure

Model: MODEL7

Dependent Variable: Trad_Epl_Rate

Number of Observations Read	81
Number of Observations Used	80
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	0.11042	0.01840	2.65	0.0221
Error	73	0.50666	0.00694		
Corrected Total	79	0.61709			

Root MSE	0.08331	R-Square	0.1789
Dependent Mean	0.58867	Adj R-Sq	0.1115
Coeff Var	14.15222		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Standardized Estimate
Intercept	1	0.57605	0.08768	6.57	<.0001	0
Total Academic Institution	1	-0.00078420	0.00077363	-1.01	0.3141	-0.16903
High education rate	1	0.30049	0.46841	0.64	0.5232	0.12584
Government Support	1	-0.19349	0.06911	-2.80	0.0065	-0.31626
Venture Capital Money	1	-1.06476E-8	9.443453E-9	-1.13	0.2632	-0.23077

Comfort Score	1	0.01010	0.01467	0.69	0.4936	0.08268
Total Population	1	0.00003589	0.00006151	0.58	0.5614	0.1057

The multiple regression results show that intensity of government support was also a significant factor of traditional industry in China. However it has a negative effect, but not a positive effect, on traditional industry, and the level of significance of it is much lower when compared to the high-tech industry sector. Other indicators were insignificant and this model can only explain 17.18% of traditional industry employment.

5 Conclusion

5.1 Comparison of the U.S. group and the China group

It is easy to tell from the result that there are many differences between the U.S. and China on the high-tech clusters issue.

The first and most obvious difference is the different leading power in the two countries. In the U.S., venture capital is prominent in while its corresponding part in China are the number of academic institutions and government power.

The second point is the opposite situation for the factors we analyzed in the two groups. It is noticeable the leading power in one country turned out to be insignificant in the other countries. Some other things made the situation more interesting. The only two factors have a positive significance on high-tech clusters in China were all not significant or had a negative significance in the U.S group, and the same thing happened with the U.S. group.

These differences imply different development and management modes of high-tech clusters in the two countries.

5.2 Explanation and discussion

5.2.1 For the U.S. group

First of all, the funding raised by venture capital is an important factor of the development of high-tech clusters in the U.S. What is noticeable is the much higher significance of it when compared to other significant factors. The standardized estimate values value of it was 0.63676 while that of the second factor is only 0.4544.

The total population factor, which generally can reflect the size and comprehensive economic level of an area, was the second most significant factor in this research. The strong correlation between this factor and the tech pole score showed the close relationship between high-tech industry and those industries active in highly developed area, especially the financial industry.

The test on the human comfort score had a better result than expected. It turned out to have a t value of 2.27, while the corresponding t value of the same variable is -4.82. It was expected that the effects of the human comfort score should be close in both high-tech and traditional sectors, since it is a basic natural condition of an area, and would be considered by most of the industries. The result showed a high human comfort score, which implies a more comfortable climate, is especially important to high-tech industry when compared to others. This may be because those high-tech industries always hire more intelligent labor force, who have higher requirement of working environment.

The result of the high education rate corresponded to the hypothesis as expected, since labor force with high intelligence is a basic factor of the high-tech industry. At the same time, strong negative relationship with a standardized estimate value of -0.64444 between the high education rate and traditional employment rate also corresponded to the facts that the traditional industries are defined as labor-intensive and less need for high educated labor force.

The most unexpected result came from the high education institution part. From the experience of Silicon Valley, the intellectual support from colleges and universities was the most important original impetus of the high-tech clusters there. However, the factors related to high education institution support turned out to have a negative relationship with the development of high-tech clusters. The reason for this phenomenon may be explained from two fields:

- 1) Many colleges and universities with more intellectual resources in the U.S. locate in rural areas rather than highly developed urban areas to have more space and a relatively quiet environment for scientific research and teaching activities. This makes the other support factors of high-tech clusters, such as capital resource and labor resource, hard to gather together near these famous colleges and universities. Since the generation of a high-tech cluster is a comprehensive process with many efforts from different fields, the low tech pole score of the area is understandable. For instance, schools such as Cornell University, the University of Illinois at Urbana-Champaign, and Purdue University, are all located in a rural place, and those MSAs all have a quite low tech pole score no more than 0.2.

- 2) The variable used in the regression is academic R&D expenditure of those schools. The initial objective of R&D expenditure is to benefit society as a whole through the new technologies and research, but not to only benefit the industry. Thus it is very possible that a large part of the R&D expenditure may had been used on research that not close to high-tech industry, or technologies cannot be applied to practice and generate industrial profit so far.

However, these two reasons may explain why academic R&D expenditure did not have a positive relationship with the tech pole score. Nor does it explain why the relation between them is negative with a relatively high standardized estimate value is open to question, and requires further research on this topic.

There is another noticeable phenomenon found from the one-by-one linear regressions research. Some of the top rated high-tech pole areas in the U.S. were exception points in the chart and did not comply with the general trend. These top rated high-tech pole areas were all build up in the early age of high-tech clusters development history, initially stimulated by high intelligent factors of the area, and had developed their own characteristic in the long history. Combined with the present important role of venture capital in the development of high-tech clusters, we have reasons to believe that the leading factor of developing high-tech clusters nowadays in U.S. has transferred from the intelligent factors to the capital factors.

5.2.2 For the China group

The most obvious character of the research of the China group is the close standardized estimate values of the two significant factors. This result showed that the developments for Chinese high-tech clusters are led by two strong powers.

The number of local colleges and universities was the factor with highest significance level picked out from the research. It showed that the development of Chinese high-tech cluster highly relied on the research abilities of academic institutes around high-tech clusters, and is similar to those U.S. high-tech clusters such as Silicon Valley and Route 128 at their early stages. This result implied that the developments of Chinese high-tech clusters are still in early stage. The result may also be explained by the location of Chinese high education Institute. Different from the U.S. universities, many of the Chinese universities locates near the center of economic activities. This may be influenced by Chinese culture concept of Confucianism which advocating and respecting education most. As a symbol of culture and education, the locations of the universities are near developed areas. What's more, a large part of Chinese universities concentrated in several highly developed areas such as Beijing, Shanghai and Guangzhou, where capital and labor force resources are also easily accessible.

The high significance of government support for high-tech clusters development was highly expected before the research. China began to develop high-tech clusters in the mid-80s, much later than Western countries. For historical reasons, China had just finished the implementation of a planned economy at that time. Under the long-term planned economy the allocation of resources for economic development relied mainly on the government. The power of government can also be told from the research on traditional industry part. Even the traditional industry is significantly influenced by the intensity of government support. The only difference between the high-tech industry sector and traditional sector is that the significance are different, with a higher standardized estimate value of 0.44907 in high-tech industry sector and a value of 0.31226 in the traditional one. The initial development of high-tech clusters in China was mainly guided by the government. The government had a decisive role in the construction of the park. Although the business management model was also set up, there was still involvement of government departments.

The influence of venture capital in the China group is at the edge of significance, mainly because the high concentration level of venture capital in those developed area such as Beijing, Shanghai and Shenzhen.

5.3 Planning implication

Since the inception of high-tech clusters in the 1950s, it has been an inevitable topic in urban developing process. This is because high-tech clusters played an important role in the transformation of scientific and technological achievements, and helped to promote high-tech enterprises, and nurture new technological revolution and new industries. Therefore, the analysis of the significance of influencing factors of high-tech clusters can be valuable to planners in practical planning process. It is useful in launching new high-tech clusters plans, or in redeveloping existing high-tech clusters.

5.3.1 Recommendations for the U.S. planners

The lack of government power in many of the U.S. high-tech clusters are considered as an advantage of the U.S. high-tech clusters' experience. However, we cannot deny that the government can also be helpful in developing the high-tech clusters, especially on providing good infrastructure for the high-tech clusters. Therefore, to better take advantage of this power in the process of planning for the high-tech clusters, however not being controlled by it, is an important lesson for the U.S. planners.

With capital's power growing, planners should pay more attention during the building up and development of high-tech clusters to attract venture capital to the potential high-tech developing area. The development of venture capital power needs the support from the environmental factors including the macro economic development environment, legal environment, policy environment, business environment, financial environment and geographical environment. Among them, the environmental factor that planners can more easily access is the policy environment. The policy environment which attracts venture capital means to develop a special strategy to encourage and attract venture capital. The methods include industrial policy, tax incentives, foreign exchange management policy, and regional investment policy according to the local conditions. The implementation of effective incentive policies which affect the fundamental economic interests of the venture capitalists can directly lead to and increase the risk investors' interest in this area. In addition, through the implementation of special policies targeted at venture capital industry can guide the direction of the venture capital power. These implementations can further improve the investment structure of this area, and promote some of the important industries or individual regional economic development objectives.

Besides, a special region in the U.S. requiring more attention on high-tech industry field is noticed in the research analysis process—the New York-Northern New Jersey-Long Island, NY-NJ-PA Metro Area. With the largest population, the best financial environment, and relatively high performance on almost all the influencing factors, this area definitely has a potential to do better on high-tech industry field, however this MSA were always one of the exception point in the linear regression chart. The good news is that mayor Bloomberg fired a shot across the bow of Silicon Valley last year, saying New York City's efforts to attract a new science and engineering campus will help the metropolis surpass the California region as the world capital of technology startups. New York's only shortage when compared to the top ranked tech pole area is in venture capital. Thus the recommended policies of the above could be applied to New York in the future.

5.3.2 Recommendations for the China planners

The result of the research clearly showed that, the leading characters in Chinese high-tech clusters are the government and academic institutes. This is decided by Chinese socio-cultural characteristics and economic system. Thus, from planners' perspective, the task is to strengthen and improve the influence from government and academic institutes.

On the one hand, as the resource of technologies and talents, the tasks of academic institutes are to receive funding from the enterprise to reduce the government's financial burden and

improve the conversion rate of scientific and technological achievements. Planners should guarantee a good policy environment for the academic institute to work.

On the other hand, planners should promote to build government-led innovation platform in the high-tech clusters, and bring the government's functions into full play during the process. Since the external environment for business innovation in China is not ideal, the government occupies a dominant position in building innovative platform for high-tech clusters which cannot be replaced by enterprises and academic institutes. The government should not only finance public-benefit projects or basic research, but also play its functions of the institutional innovation and policy arrangements in the region, in order to provide a good system and policy environment for full and efficient interaction between the various actors in high tech innovation.

6 Reference

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7 Appendix

7.1 SAS scripts for each models

7.1.1 Model 1:

```
proc reg data=us;
```

```
model tech_pole_score = tot_aca_r_d hi_edu_rate gov_support vc_money comfort_score  
tot_pop / stb;
```

```
run;
```

7.1.2 Model 2:

```
proc reg data=us;
```

```
model tech_pole_score = tot_aca_r_d hi_edu_rate vc_money comfort_score tot_pop / stb;
```

```
run;
```

7.1.3 Model 3:

```
proc reg data=us;
```

```
model trad_epl_rate = tot_aca_r_d hi_edu_rate gov_support vc_money comfort_score tot_pop  
/ stb;
```

```
run;
```

7.1.4 Model 4:

```
proc reg data=china;
```

```
model Hitech_Epl_Rate = Aca_Num Hi_Edu_Rate Gov_Support Vc_money Comfort_score  
Tot_pop / stb;
```

```
run;
```

7.1.5 Model 5:

```
proc reg data=china;
```

```
model Hitech_Epl_Rate = Aca_Num Gov_Support Vc_money/ stb;
```

```
run;
```

7.1.6 Model 6:

```
proc reg data=china;
```

```
model Hitech_Epl_Rate = Aca_Num Gov_Support/ stb;
```

```
run;
```

7.1.7 Model 7:

```
proc reg data=china;
```

```
model Trad_Epl_Rate = Aca_Num Hi_Edu_Rate Gov_Support Vc_money Comfort_score  
Tot_pop / stb;
```

```
run;
```

7.2 Data tables

7.2.1 Data for the U.S. Group

CBSA	MSA	Tech Pole Score	Traditional Industry Employment Rate	Total Academic R&D Expenditure	High Education Rate of Labor	Intensity of Government Support	Money raised by VC	Comfort Score	Total Population
10180	Abilene, TX Metro Area	0.1	32.29%	386	25.09%	79.79%	0	5	164,941
10420	Akron, OH Metro Area	0.5	40.21%	70840	33.85%	50.42%	0	3	702,951
10500	Albany, GA Metro Area	0.1	38.91%	1206	20.49%	87.56%	0	5	162,659
10580	Albany-Schenectady-Troy, NY Metro Area	2.1	30.09%	443078	38.29%	57.38%	23.26	3	870,832
10740	Albuquerque, NM Metro Area	5.2	32.65%	201769	32.99%	68.58%	9.31	4	892,014
10780	Alexandria, LA Metro Area	0	35.81%	0	21.47%	0.00%	0	5	154,120
10900	Allentown-Bethlehem-Easton, PA-NJ Metro Area	0.7	40.63%	33719	32.42%	79.59%	64.57	4	822,141
11020	Altoona, PA Metro Area	0.1	47.69%	0	21.74%	0.00%	0	4	127,031
11100	Amarillo, TX Metro Area	0.1	42.72%	5366	27.72%	74.51%	0	4	251,915
11180	Ames, IA Metro Area	0.1	31.90%	224311	52.23%	63.98%	0	3	89,575
11260	Anchorage, AK Metro Area	0.7	34.40%	7638	34.78%	87.81%	0	3	382,964
11300	Anderson, IN Metro Area	0.1	39.34%	0	20.91%	0.00%	0	4	131,642
11340	Anderson, SC Metro Area	0	49.80%	0	20.82%	0.00%	0	5	187,269
11460	Ann Arbor, MI Metro Area	1.5	26.37%	1012955	55.77%	63.62%	7.2	3	345,290
11500	Anniston-Oxford, AL Metro Area	0.2	41.29%	224	18.26%	55.80%	0	5	118,510
11540	Appleton, WI Metro Area	0.2	50.14%	458	30.29%	88.86%	0	3	225,952
11700	Asheville, NC Metro Area	0.2	35.53%	2933	32.46%	88.34%	52	4	422,752
12020	Athens-Clarke County, GA Metro Area	0.1	34.85%	349730	42.38%	44.85%	0	5	192,738
12060	Atlanta-Sandy Springs-	14	37.87%	1119890	38.28%	63.33%	246.13	5	5,288,302

	Marietta, GA Metro Area								
12100	Atlantic City-Hammonton, NJ Metro Area	0.1	26.81%	0	26.37%	0.00%	0	4	274,685
12220	Auburn-Opelika, AL Metro Area	0.1	34.14%	515547	35.24%	55.16%	0	5	140,780
12260	Augusta-Richmond County, GA-SC Metro Area	0.3	41.47%	70768	28.24%	69.18%	0	5	560,293
12420	Austin-Round Rock-San Marcos, TX Metro Area	11.6	34.67%	581940	43.05%	66.47%	168.27	5	1,728,307
12580	Baltimore-Towson, MD Metro Area	8.3	29.92%	1917108	40.69%	85.08%	85.99	4	2,714,183
12620	Bangor, ME Metro Area	0.2	34.23%	100580	29.11%	47.60%	0	3	153,849
12700	Barnstable Town, MA Metro Area	0.2	32.09%	157289	39.68%	82.09%	0	3	215,937
12940	Baton Rouge, LA Metro Area	0.7	39.65%	408171	31.49%	61.39%	6	5	804,406
12980	Battle Creek, MI Metro Area	0	45.91%	0	20.79%	0.00%	0	3	136,072
13020	Bay City, MI Metro Area	0.1	42.53%	561	25.06%	15.86%	0	3	107,703
13140	Beaumont-Port Arthur, TX Metro Area	0.4	43.72%	5376	18.44%	91.07%	0	5	389,068
13380	Bellingham, WA Metro Area	0.2	36.36%	9055	35.27%	62.30%	0	3	201,628
13460	Bend, OR Metro Area	0.2	31.51%	0	29.33%	0.00%	0	4	157,894
13740	Billings, MT Metro Area	0.2	41.25%	629	35.72%	81.56%	0	3	157,365
13780	Binghamton, NY Metro Area	2.4	38.39%	66050	30.00%	35.32%	0	3	251,321
13820	Birmingham-Hoover, AL Metro Area	1.1	39.55%	431732	31.72%	69.60%	0	5	1,128,978
13900	Bismarck, ND Metro Area	0.1	38.86%	0	37.25%	0.00%	0	3	109,266
13980	Blacksburg-Christiansburg-Radford, VA Metro Area	0.2	32.56%	397043	36.10%	62.65%	100	4	161,768

14020	Bloomington, IN Metro Area	0.6	32.98%	440815	37.95%	46.19%	0	4	192,696
14060	Bloomington-Normal, IL Metro Area	0.3	28.05%	5888	45.82%	72.93%	0	4	169,832
14260	Boise City-Nampa, ID Metro Area	2.5	39.41%	11955	32.03%	83.49%	0	4	619,694
14460	Boston-Cambridge-Quincy, MA-NH Metro Area	45.2	30.64%	1888500	49.38%	75.48%	1931.99	4	4,560,689
14500	Boulder, CO Metro Area	9.3	31.38%	648417	60.13%	81.40%	102.66	3	295,166
14540	Bowling Green, KY Metro Area	0	42.32%	8516	32.99%	82.14%	0	4	127,280
14740	Bremerton-Silverdale, WA Metro Area	0.2	35.62%	0	30.51%	0.00%	10	3	251,809
14860	Bridgeport-Stamford-Norwalk, CT Metro Area	4.3	31.63%	2577	47.47%	21.15%	16.74	4	918,714
15180	Brownsville-Harlingen, TX Metro Area	0	33.75%	0	18.21%	0.00%	0	4	408,054
15260	Brunswick, GA Metro Area	0	33.95%	0	23.01%	0.00%	0	5	107,890
15380	Buffalo-Niagara Falls, NY Metro Area	1.5	35.80%	341261	34.82%	51.06%	17.29	3	1,135,198
15500	Burlington, NC Metro Area	0.2	41.19%	0	22.40%	0.00%	0	5	151,528
15540	Burlington-South Burlington, VT Metro Area	1.3	35.42%	123171	44.70%	75.68%	0	3	211,035
15940	Canton-Massillon, OH Metro Area	0.1	42.01%	0	23.76%	0.00%	0	4	403,238
15980	Cape Coral-Fort Myers, FL Metro Area	0.2	35.52%	3915	23.10%	88.74%	0	4	620,151
16180	Carson City, NV Metro Area	0	#VALUE!	0	24.44%	0.00%	0	4	55,226
16220	Casper, WY Metro Area	0	45.66%	0	18.69%	0.00%	0	3	75,507

16300	Cedar Rapids, IA Metro Area	1.2	45.58%	286	32.47%	52.10%	0	3	258,223
16580	Champaign-Urbana, IL Metro Area	0.2	28.63%	563710	41.63%	57.44%	1.2	4	234,445
16620	Charleston, WV Metro Area	0.2	37.20%	4017	27.86%	93.03%	0	4	304,571
16700	Charleston-North Charleston-Summerville, SC Metro Area	0.8	36.60%	221719	36.29%	53.38%	7.2	5	667,741
16740	Charlotte-Gastonia-Rock Hill, NC-SC Metro Area	2.4	39.20%	26687	36.82%	62.87%	0	3	1,764,313
16820	Charlottesville, VA Metro Area	0.4	26.95%	261604	48.45%	83.85%	7.5	4	199,776
16860	Chattanooga, TN-GA Metro Area	0.3	41.70%	0	27.76%	0.00%	0	4	530,205
16940	Cheyenne, WY Metro Area	0.1	32.51%	0	27.29%	0.00%	0	3	92,127
16980	Chicago-Joliet-Naperville, IL-IN-WI Metro Area	13.3	37.65%	1440464	39.34%	65.79%	296.04	3	9,474,211
17020	Chico, CA Metro Area	0.1	35.05%	1889	24.77%	73.21%	0	5	220,072
17140	Cincinnati-Middletown, OH-KY-IN Metro Area	2.9	40.01%	388329	34.49%	69.55%	25.5	4	2,133,203
17300	Clarksville, TN-KY Metro Area	0.1	41.18%	0	22.58%	0.00%	0	4	274,695
17420	Cleveland, TN Metro Area	0.1	46.16%	0	20.90%	0.00%	0	4	115,716
17460	Cleveland-Elyria-Mentor, OH Metro Area	2.3	37.53%	430183	32.66%	78.87%	33.17	3	2,075,758
17660	Coeur d'Alene, ID Metro Area	0.1	39.30%	0	25.04%	0.00%	0	4	138,901
17780	College Station-Bryan, TX Metro Area	0.2	31.30%	714286	38.22%	59.74%	0	5	230,141
17820	Colorado Springs, CO Metro Area	4	31.80%	49117	36.03%	79.66%	0	3	648,943
17860	Columbia, MO Metro Area	0.1	28.35%	245058	54.23%	57.11%	1.5	4	172,319

17900	Columbia, SC Metro Area	0.5	35.48%	188275	35.05%	58.90%	0	5	770,410
17980	Columbus, GA-AL Metro Area	0.9	33.40%	0	25.30%	0.00%	0	5	292,141
18020	Columbus, IN Metro Area	0.1	#VALUE!	0	30.96%	0.00%	0	4	76,855
18140	Columbus, OH Metro Area	4.4	35.37%	717189	38.18%	64.12%	0.68	4	1,840,631
18580	Corpus Christi, TX Metro Area	0.2	37.75%	27909	22.94%	60.07%	0	5	428,217
18700	Corvallis, OR Metro Area	0.6	31.62%	209345	53.17%	76.94%	0	4	85,575
19060	Cumberland, MD-WV Metro Area	0	40.15%	0	21.14%	0.00%	0	4	103,239
19100	Dallas-Fort Worth-Arlington, TX Metro Area	21.8	39.34%	587027	34.49%	63.00%	98.78	5	6,402,922
19140	Dalton, GA Metro Area	0.4	60.54%	0	13.71%	0.00%	0	5	142,493
19180	Danville, IL Metro Area	0	47.90%	0	17.33%	0.00%	0	4	81,551
19260	Danville, VA Metro Area	0.1	49.30%	0	17.82%	0.00%	0	4	106,416
19340	Davenport-Moline-Rock Island, IA-IL Metro Area	0.2	43.88%	3620	29.73%	40.19%	0	3	382,382
19380	Dayton, OH Metro Area	2	37.56%	172254	28.81%	74.54%	0	4	841,310
19460	Decatur, AL Metro Area	0.1	51.25%	0	17.75%	0.00%	0	5	153,968
19500	Decatur, IL Metro Area	0	45.00%	0	25.80%	0.00%	0	4	110,715
19660	Deltona-Daytona Beach-Ormond Beach, FL Metro Area	0.3	38.35%	10899	22.51%	81.68%	0	5	494,527
19740	Denver-Aurora-Broomfield, CO Metro Area	11.9	35.11%	52677	42.32%	69.34%	170.19	4	2,560,529
19780	Des Moines-West Des Moines, IA Metro Area	0.7	33.99%	1567	36.89%	26.80%	0	4	570,358
19820	Detroit-Warren-Livonia, MI Metro Area	2.7	39.74%	265565	33.16%	50.18%	40.54	4	4,291,843

20020	Dothan, AL Metro Area	0.1	46.04%	0	20.61%	0.00%	0	5	146,010
20100	Dover, DE Metro Area	0	37.02%	9335	26.99%	94.67%	1.5	4	162,912
20220	Dubuque, IA Metro Area	0.2	42.15%	0	31.07%	0.00%	0	3	93,880
20260	Duluth, MN-WI Metro Area	0.1	34.87%	3849	29.86%	85.68%	0	3	280,035
20500	Durham-Chapel Hill, NC Metro Area	9.7	27.67%	1456411	48.39%	65.92%	118.23	5	505,933
20740	Eau Claire, WI Metro Area	0.2	41.99%	1589	29.91%	75.71%	0	3	161,443
20940	El Centro, CA Metro Area	0	42.21%	0	18.67%	0.00%	0	5	175,234
21340	El Paso, TX Metro Area	0.3	39.02%	56635	24.52%	56.71%	0	5	122,347
21060	Elizabethtown, KY Metro Area	0.1	58.26%	0	23.38%	0.00%	0	4	197,646
21140	Elkhart-Goshen, IN Metro Area	0.1	39.21%	0	18.65%	0.00%	0	4	88,824
21300	Elmira, NY Metro Area	0.1	37.24%	0	25.34%	0.00%	0	4	804,338
21500	Erie, PA Metro Area	0.2	40.94%	825	27.96%	42.91%	0	4	280,686
21660	Eugene-Springfield, OR Metro Area	0.4	35.44%	75869	30.36%	81.46%	0	4	351,983
21780	Evansville, IN-KY Metro Area	0.6	49.17%	0	25.47%	0.00%	0	4	357,948
21820	Fairbanks, AK Metro Area	0	36.48%	123420	30.59%	88.02%	0	2	98,314
22020	Fargo, ND-MN Metro Area	0.4	37.91%	113744	40.60%	71.23%	0	3	209,144
22140	Farmington, NM Metro Area	0	45.19%	0	17.52%	0.00%	0	4	130,145
22180	Fayetteville, NC Metro Area	0.1	33.02%	1613	27.81%	96.28%	0	5	367,733
22220	Fayetteville-Springdale-Rogers, AR-MO Metro Area	0.4	51.04%	105446	29.44%	73.74%	0	5	465,780
22380	Flagstaff, AZ Metro Area	0.1	32.94%	26183	34.38%	66.84%	13.4	3	134,651
22420	Flint, MI Metro Area	0.2	40.52%	4294	23.35%	71.61%	0	3	424,926
22500	Florence, SC Metro Area	0.1	39.47%	0	23.04%	0.00%	0	5	205,705
22520	Florence-Muscle Shoals, AL	0	49.62%	0	22.61%	0.00%	0	5	147,112

	Metro Area								
22540	Fond du Lac, WI Metro Area	0.1	50.14%	0	18.96%	0.00%	0	3	101,665
22660	Fort Collins-Loveland, CO Metro Area	1.5	35.20%	304397	49.89%	75.74%	16	3	300,637
22900	Fort Smith, AR-OK Metro Area	0.1	47.64%	0	19.63%	0.00%	0	5	299,749
23060	Fort Wayne, IN Metro Area	0.7	46.27%	0	28.57%	0.00%	0	4	415,013
23420	Fresno, CA Metro Area	0.3	42.13%	9837	23.88%	70.09%	0	5	933,248
23460	Gadsden, AL Metro Area	0	#VALUE!	0	16.90%	0.00%	0	5	104,462
23540	Gainesville, FL Metro Area	0.2	24.08%	592082	41.99%	55.87%	0	5	266,321
23580	Gainesville, GA Metro Area	0.1	47.56%	0	25.52%	0.00%	0	5	180,253
24020	Glens Falls, NY Metro Area	0.3	40.52%	0	27.49%	0.00%	0	4	128,985
24140	Goldsboro, NC Metro Area	0	46.74%	0	17.02%	0.00%	0	3	122,907
24220	Grand Forks, ND-MN Metro Area	0	38.62%	71656	32.21%	76.49%	0	3	99,586
24300	Grand Junction, CO Metro Area	0	38.06%	687	28.39%	72.63%	0	4	146,313
24340	Grand Rapids-Wyoming, MI Metro Area	0.6	44.00%	3061	31.23%	48.91%	7.96	3	774,540
24500	Great Falls, MT Metro Area	0	36.08%	0	29.95%	0.00%	0	3	81,519
24540	Greeley, CO Metro Area	0.1	45.69%	2387	28.93%	79.89%	0	3	254,270
24580	Green Bay, WI Metro Area	0.1	47.19%	979	26.74%	67.62%	0	3	306,730
24660	Greensboro-High Point, NC Metro Area	0.7	43.85%	38934	30.78%	71.29%	0	4	725,282
24780	Greenville, NC Metro Area	0.1	36.42%	24177	31.01%	80.36%	0	5	190,201
24860	Greenville-Mauldin-Easley, SC Metro Area	1	42.71%	188238	31.91%	40.27%	0	5	638,576
25060	Gulfport-Biloxi, MS Metro	0.1	34.33%	0	24.00%	0.00%	0	5	250,196

	Area								
25180	Hagerstown-Martinsburg, MD-WV Metro Area	0.1	40.56%	0	24.74%	0.00%	0	4	267,239
25260	Hanford-Corcoran, CA Metro Area	0	43.68%	0	13.41%	0.00%	0	5	153,174
25420	Harrisburg-Carlisle, PA Metro Area	0.8	36.86%	1713	34.23%	67.02%	0	4	550,076
25500	Harrisonburg, VA Metro Area	0.1	43.67%	5305	29.20%	75.55%	0	4	125,454
25540	Hartford-West Hartford-East Hartford, CT Metro Area	4.7	33.60%	236907	39.87%	57.34%	6.95	4	1,212,956
25620	Hattiesburg, MS Metro Area	0	38.86%	46744	30.89%	91.78%	0	5	146,199
25860	Hickory-Lenoir-Morganton, NC Metro Area	0.1	51.09%	0	21.04%	0.00%	0	5	365,397
25980	Hinesville-Fort Stewart, GA Metro Area	0	#VALUE!	0	23.21%	0.00%	0	5	74,778
26100	Holland-Grand Haven, MI Metro Area	0.4	47.37%	6167	32.48%	44.07%	0	3	264,055
26180	Honolulu, HI Metro Area	0.9	31.03%	290707	36.03%	75.90%	0	4	955,775
26300	Hot Springs, AR Metro Area	0.1	#VALUE!	0	18.90%	0.00%	0	5	96,145
26380	Houma-Bayou Cane-Thibodaux, LA Metro Area	0.1	51.64%	1572	15.57%	46.56%	0	5	208,189
26420	Houston-Sugar Land-Baytown, TX Metro Area	11.6	43.80%	1625360	31.54%	63.81%	84.28	5	5,977,092
26580	Huntington-Ashland, WV-KY-OH Metro Area	0.1	38.06%	22437	23.05%	80.81%	0	4	287,611
26620	Huntsville, AL Metro Area	10.5	35.41%	86610	39.85%	77.11%	0	5	419,181
26820	Idaho Falls, ID Metro Area	0.2	38.67%	0	25.33%	0.00%	0	4	132,610
26900	Indianapolis-Carmel, IN	4.9	40.25%	0	35.87%	0.00%	129.79	4	1,759,229

	Metro Area								
26980	Iowa City, IA Metro Area	0.3	29.60%	329901	52.76%	77.68%	0	3	152,918
27060	Ithaca, NY Metro Area	0.2	20.28%	672839	59.11%	65.93%	1.4	4	101,620
27100	Jackson, MI Metro Area	0	44.81%	0	21.62%	0.00%	0	3	160,201
27140	Jackson, MS Metro Area	0.3	34.86%	48320	33.49%	83.42%	0	5	540,140
27180	Jackson, TN Metro Area	0	38.11%	0	26.37%	0.00%	0	4	114,241
27260	Jacksonville, FL Metro Area	1.5	35.03%	5271	29.64%	83.74%	0	5	1,350,198
27340	Jacksonville, NC Metro Area	0	28.80%	0	21.86%	0.00%	0	5	179,471
27500	Janesville, WI Metro Area	0	47.88%	0	22.43%	0.00%	0	3	160,310
27620	Jefferson City, MO Metro Area	0.1	34.11%	8011	31.51%	100.00%	0	4	149,872
27740	Johnson City, TN Metro Area	0.1	35.87%	9189	33.63%	73.68%	0	4	198,974
27780	Johnstown, PA Metro Area	0.2	40.28%	2915	26.29%	100.00%	0	4	143,498
27860	Jonesboro, AR Metro Area	0.1	45.13%	8622	23.52%	88.09%	0	5	120,365
27900	Joplin, MO Metro Area	0.1	46.55%	0	20.68%	0.00%	0	4	175,887
28020	Kalamazoo-Portage, MI Metro Area	0.6	42.64%	13714	34.53%	66.89%	0.59	3	326,924
28100	Kankakee-Bradley, IL Metro Area	0.1	42.94%	0	21.24%	0.00%	0	4	113,502
28140	Kansas City, MO-KS Metro Area	8.4	36.46%	28492	37.83%	59.90%	33.47	4	2,035,747
28420	Kennewick-Pasco-Richland, WA Metro Area	1.4	46.94%	0	25.28%	0.00%	0	3	255,678
28660	Killeen-Temple-Fort Hood, TX Metro Area	0.3	30.81%	0	22.00%	0.00%	0	5	408,366
28700	Kingsport-Bristol-Bristol, TN-VA Metro Area	0.3	45.76%	0	24.01%	0.00%	0	4	310,695
28740	Kingston, NY Metro Area	0.1	35.25%	209	33.76%	90.43%	0	4	182,435

28940	Knoxville, TN Metro Area	0.8	39.87%	284896	34.30%	70.45%	0	4	699,180
29020	Kokomo, IN Metro Area	0.1	49.69%	0	23.08%	0.00%	0	4	100,485
29100	La Crosse, WI-MN Metro Area	0.1	42.44%	3010	34.07%	58.31%	0	3	133,896
29140	Lafayette, IN Metro Area	0.1	36.94%	453799	36.53%	49.62%	0	4	202,782
29180	Lafayette, LA Metro Area	0.4	41.24%	68018	30.38%	39.77%	0	5	274,265
29340	Lake Charles, LA Metro Area	0.1	40.69%	807	25.72%	67.41%	0	5	198,628
29460	Lakeland-Winter Haven, FL Metro Area	0.1	40.24%	0	21.41%	0.00%	9.02	4	602,788
29540	Lancaster, PA Metro Area	0.2	48.95%	6058	27.71%	58.65%	0	4	520,156
29620	Lansing-East Lansing, MI Metro Area	0.3	32.40%	373184	33.63%	55.46%	0	3	464,076
29700	Laredo, TX Metro Area	0	40.54%	1227	20.99%	95.27%	0	5	251,632
29740	Las Cruces, NM Metro Area	0.2	32.34%	149798	28.32%	72.16%	0	4	210,538
29820	Las Vegas-Paradise, NV Metro Area	0.9	28.29%	39148	23.29%	85.97%	7	5	1,954,260
29940	Lawrence, KS Metro Area	0	30.24%	226862	53.28%	59.45%	0	4	111,130
30020	Lawton, OK Metro Area	0	36.23%	0	20.41%	0.00%	0	5	125,368
30140	Lebanon, PA Metro Area	0.1	42.75%	0	23.30%	0.00%	0	4	133,688
30300	Lewiston, ID-WA Metro Area	0	#VALUE!	0	21.37%	0.00%	0	4	60,946
30340	Lewiston-Auburn, ME Metro Area	0	43.85%	1117	23.93%	68.49%	0	3	107,623
30460	Lexington-Fayette, KY Metro Area	1.3	37.57%	373364	36.03%	51.83%	0.02	4	473,547
30620	Lima, OH Metro Area	0.1	46.80%	167	21.54%	67.07%	0	4	106,205
30700	Lincoln, NE Metro Area	0.6	34.22%	366507	38.24%	42.87%	0	4	303,151
30780	Little Rock-North Little Rock-Conway, AR Metro Area	1.5	34.79%	117746	31.41%	63.48%	0	5	701,713

30860	Logan, UT-ID Metro Area	0.3	45.09%	143010	35.34%	80.89%	0	4	125,791
30980	Longview, TX Metro Area	0.1	46.71%	696	18.88%	68.68%	0	5	214,602
31020	Longview, WA Metro Area	0	46.09%	0	17.50%	0.00%	0	3	102,501
31100	Los Angeles-Long Beach-Santa Ana, CA Metro Area	40.2	36.74%	2213250	34.58%	66.81%	854.5622	5	12,849,383
31140	Louisville/Jefferson County, KY-IN Metro Area	0.8	39.44%	152063	31.27%	58.25%	6.98	4	1,287,271
31180	Lubbock, TX Metro Area	0.3	35.83%	117374	31.72%	51.24%	0	5	288,462
31340	Lynchburg, VA Metro Area	0.1	41.93%	0	24.47%	0.00%	0	4	251,016
31420	Macon, GA Metro Area	0.1	37.03%	21858	26.60%	62.01%	0	5	227,880
31460	Madera-Chowchilla, CA Metro Area	0	54.15%	0	18.35%	0.00%	0	5	151,408
31540	Madison, WI Metro Area	2.1	32.68%	952804	46.75%	57.43%	43.7	3	569,923
31700	Manchester-Nashua, NH Metro Area	3.7	42.20%	0	39.38%	0.00%	38.03	3	401,057
31900	Mansfield, OH Metro Area	0.1	46.43%	0	18.33%	0.00%	0	3	124,177
32580	McAllen-Edinburg-Mission, TX Metro Area	0.1	37.28%	12583	20.15%	89.34%	0	5	780,087
32780	Medford, OR Metro Area	0.1	37.49%	584	26.21%	77.74%	10	4	203,462
32820	Memphis, TN-MS-AR Metro Area	0.7	41.04%	46738	29.28%	45.03%	3.23	5	1,316,579
32900	Merced, CA Metro Area	0	50.97%	0	13.34%	0.00%	0	5	256,778
33100	Miami-Fort Lauderdale-Pompano Beach, FL Metro Area	1.7	34.78%	323531	31.71%	67.32%	54.5	5	5,582,351
33140	Michigan City-La Porte, IN Metro Area	0.1	47.94%	91278	22.59%	66.04%	0	5	111,465
33260	Midland, TX Metro Area	0.2	52.33%	0	21.82%	0.00%	50	5	136,975

33340	Milwaukee-Waukesha-West Allis, WI Metro Area	2.6	39.60%	234872	36.86%	64.44%	8.02	3	1,557,244
33460	Minneapolis-St. Paul-Bloomington, MN-WI Metro Area	11.9	38.46%	750167	42.26%	61.18%	149.08	3	3,286,195
33540	Missoula, MT Metro Area	0.1	32.36%	59505	42.73%	65.41%	2.2	3	109,494
33660	Mobile, AL Metro Area	0.4	41.65%	29197	25.53%	56.07%	0	5	413,277
33700	Modesto, CA Metro Area	0.1	48.85%	0	18.95%	0.00%	0	5	515,358
33740	Monroe, LA Metro Area	0.1	39.33%	4794	23.05%	81.89%	0	5	176,664
33780	Monroe, MI Metro Area	0	46.49%	0	21.61%	0.00%	0	3	151,932
33860	Montgomery, AL Metro Area	0.6	36.99%	17164	32.74%	87.97%	0	5	376,208
34060	Morgantown, WV Metro Area	0	33.53%	139592	37.78%	50.06%	1.05	4	130,288
34100	Morristown, TN Metro Area	0	50.18%	0	18.45%	0.00%	0	4	136,787
34580	Mount Vernon-Anacortes, WA Metro Area	0	44.31%	0	22.62%	0.00%	0	3	117,102
34620	Muncie, IN Metro Area	0.1	34.93%	6621	30.13%	35.87%	0	4	117,669
34740	Muskegon-Norton Shores, MI Metro Area	0	46.29%	0	19.20%	0.00%	0	3	172,068
34820	Myrtle Beach-North Myrtle Beach-Conway, SC Metro Area	0.1	34.08%	0	24.77%	0.00%	0	5	270,430
34900	Napa, CA Metro Area	0.1	41.14%	0	30.22%	0.00%	0	5	136,858
34940	Naples-Marco Island, FL Metro Area	0.1	38.55%	0	27.89%	0.00%	0	5	322,472
34980	Nashville-Davidson--Murfreesboro--Franklin, TN Metro Area	1.7	36.99%	478209	34.92%	78.47%	22.03	4	1,593,050

35300	New Haven-Milford, CT Metro Area	3.1	34.23%	511725	36.82%	75.58%	1.3	4	862,989
35380	New Orleans-Metairie-Kenner, LA Metro Area	0.9	36.71%	166055	31.53%	76.09%	0	5	1,173,327
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA Metro Area	16.8	31.29%	5805897	42.01%	67.96%	1287.34	4	18,919,983
35660	Niles-Benton Harbor, MI Metro Area	0.1	46.05%	494	25.39%	34.82%	0	3	156,805
35980	Norwich-New London, CT Metro Area	1	34.78%	1584	34.68%	93.37%	0.23	4	703,309
36100	Ocala, FL Metro Area	0.2	39.12%	0	19.13%	0.00%	0	5	331,290
36140	Ocean City, NJ Metro Area	0	31.06%	0	31.59%	0.00%	0	4	97,253
36220	Odessa, TX Metro Area	0	48.35%	797	14.75%	24.84%	0	5	137,145
36260	Ogden-Clearfield, UT Metro Area	0.6	38.22%	777	32.17%	45.69%	0	4	551,173
36420	Oklahoma City, OK Metro Area	1.2	36.07%	201821	32.22%	58.72%	0	5	1,257,845
36500	Olympia, WA Metro Area	0.1	30.53%	672	33.50%	96.88%	0	3	253,087
36540	Omaha-Council Bluffs, NE-IA Metro Area	1.6	35.86%	27104	37.75%	57.00%	0	4	868,238
36740	Orlando-Kissimmee-Sanford, FL Metro Area	4.7	32.39%	113433	31.59%	70.55%	45.51	4	2,140,795
36780	Oshkosh-Neenah, WI Metro Area	0.2	46.88%	1067	24.03%	60.07%	0	3	167,059
36980	Owensboro, KY Metro Area	0	50.92%	0	19.17%	0.00%	0	4	115,857
37100	Oxnard-Thousand Oaks-Ventura, CA Metro Area	3.8	38.01%	606	34.04%	25.74%	0	5	825,706

37340	Palm Bay-Melbourne-Titusville, FL Metro Area	4.1	37.80%	10389	29.24%	84.03%	11.71	5	543,573
37380	Palm Coast, FL Metro Area		#VALUE!	0	24.47%	0.00%	0	5	95,928
37460	Panama City-Lynn Haven-Panama City Beach, FL Metro Area	0.2	33.08%	0	20.72%	0.00%	0	5	169,272
37620	Parkersburg-Marietta-Vienna, WV-OH Metro Area	0.1	42.60%	0	20.03%	0.00%	0	4	162,723
37700	Pascagoula, MS Metro Area	0.1	47.95%	0	18.26%	0.00%	0	5	162,384
37860	Pensacola-Ferry Pass-Brent, FL Metro Area	0.3	32.43%	3274	27.72%	91.97%	0	5	450,009
37900	Peoria, IL Metro Area	0.3	43.10%	1598	31.24%	23.97%	0	4	378,712
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	14.4	33.91%	1195695	39.44%	71.81%	144.26	4	5,971,483
38060	Phoenix-Mesa-Glendale, AZ Metro Area	10.4	36.26%	281588	30.71%	57.34%	49.68	5	4,211,213
38220	Pine Bluff, AR Metro Area	0	44.02%	7422	15.45%	55.62%	0	5	99,871
38300	Pittsburgh, PA Metro Area	4.3	37.12%	852211	36.89%	77.33%	86.56	4	2,356,381
38340	Pittsfield, MA Metro Area	0.2	34.01%	4907	32.99%	39.92%	0.37	3	131,144
38540	Pocatello, ID Metro Area	0	40.54%	20524	29.86%	62.33%	0	3	90,438
38940	Port St. Lucie, FL Metro Area	0.2	37.91%	0	24.01%	0.00%	0	5	425,082
38860	Portland-South Portland-Biddeford, ME Metro Area	0.9	35.17%	25304	38.06%	62.02%	0	3	513,899
38900	Portland-Vancouver-Hillsboro, OR-WA Metro Area	9.6	39.87%	349282	36.80%	77.31%	84.06	4	2,232,496
39100	Poughkeepsie-Newburgh-	1.3	36.03%	11439	35.99%	87.91%	0	4	670,932

	Middletown, NY Metro Area								
39140	Prescott, AZ Metro Area	0.1	33.10%	0	20.76%	0.00%	0	5	211,061
39300	Providence-New Bedford-Fall River, RI-MA Metro Area	2.2	37.19%	265665	34.51%	64.69%	9.27	4	1,601,498
39340	Provo-Orem, UT Metro Area	1.9	35.80%	25497	37.80%	70.86%	48.53	4	529,970
39380	Pueblo, CO Metro Area	0	39.80%	328	22.18%	82.93%	0	4	159,477
39460	Punta Gorda, FL Metro Area	0	32.94%	0	24.30%	0.00%	0	5	159,990
39540	Racine, WI Metro Area	0.1	49.80%	0	27.36%	0.00%	0	3	195,510
39580	Raleigh-Cary, NC Metro Area	5.3	35.09%	382885	45.82%	66.16%	75.89	5	1,137,552
39660	Rapid City, SD Metro Area	0.1	33.15%	14373	31.15%	89.08%	0	3	126,802
39740	Reading, PA Metro Area	0.3	43.29%	0	27.15%	0.00%	0.05	4	411,850
39820	Redding, CA Metro Area	0.1	34.61%	0	24.97%	0.00%	0	5	177,291
39900	Reno-Sparks, NV Metro Area	0.3	34.07%	142868	28.75%	71.37%	0	4	426,448
40060	Richmond, VA Metro Area	1.5	34.86%	162908	36.83%	72.48%	27.02	4	1,261,317
40140	Riverside-San Bernardino-Ontario, CA Metro Area	1.6	41.99%	177447	21.97%	56.00%	0	5	4,245,773
40220	Roanoke, VA Metro Area	0.3	39.31%	2524	32.82%	29.56%	59	4	308,893
40340	Rochester, MN Metro Area	0.7	31.82%	0	39.11%	0.00%	5.1	3	186,302
40380	Rochester, NY Metro Area	3.7	37.26%	426876	38.54%	77.08%	8.67	3	1,054,445
40420	Rockford, IL Metro Area	0.2	46.04%	0	24.42%	0.00%	0	3	349,287
40580	Rocky Mount, NC Metro Area	0.3	46.12%	0	16.50%	0.00%	0	5	152,477
40660	Rome, GA Metro Area	0	34.10%	0	24.06%	0.00%	0	5	96,274
40900	Sacramento--Arden-Arcade--Roseville, CA Metro Area	3.7	32.26%	11734	33.60%	75.97%	30.2	5	2,154,391
40980	Saginaw-Saginaw Township North, MI Metro Area	0.2	42.25%	0	23.04%	0.00%	0	3	199,911
41420	Salem, OR Metro Area	0.1	39.11%	951	24.99%	55.63%	0	4	391,721
41500	Salinas, CA Metro Area	0.1	43.38%	81800	23.41%	98.24%	7.31	5	416,682

41620	Salt Lake City, UT Metro Area	5.6	39.49%	331137	31.66%	58.50%	55.08	4	1,128,988
41660	San Angelo, TX Metro Area	0.2	36.35%	1155	20.81%	72.38%	0	5	112,484
41700	San Antonio-New Braunfels, TX Metro Area	3	34.61%	0	28.60%	0.00%	7.2	5	2,157,897
41740	San Diego-Carlsbad-San Marcos, CA Metro Area	19.3	33.13%	1347382	37.89%	66.44%	374.65	5	3,105,989
41860	San Francisco-Oakland-Fremont, CA Metro Area	16.1	31.69%	2365111	48.49%	50.10%	3225.4	4	4,345,320
41940	San Jose-Sunnyvale-Santa Clara, CA Metro Area	100	40.17%	747588	49.92%	72.20%	2293.12	5	1,843,255
42020	San Luis Obispo-Paso Robles, CA Metro Area	0.2	37.87%	19420	32.91%	75.53%	9	5	270,113
41780	Sandusky, OH Metro Area	0	40.19%	0	24.13%	0.00%	0	4	77,070
42060	Santa Barbara-Santa Maria-Goleta, CA Metro Area	17.7	37.83%	215728	31.22%	54.57%	30.17	4	424,712
42100	Santa Cruz-Watsonville, CA Metro Area	0.3	37.91%	144052	35.60%	55.62%	12.5	5	263,054
42140	Santa Fe, NM Metro Area	0.1	27.80%	0	39.35%	0.00%	2.87	4	144,606
42220	Santa Rosa-Petaluma, CA Metro Area	1	39.93%	525	33.02%	79.24%	14.98	5	485,120
42540	Scranton--Wilkes-Barre, PA Metro Area	0.6	39.97%	640	28.86%	76.88%	0.55	4	564,446
42660	Seattle-Tacoma-Bellevue, WA Metro Area	46.4	37.78%	782218	40.99%	81.21%	213.07	4	3,449,059
43100	Sheboygan, WI Metro Area	0	56.05%	0	24.27%	0.00%	0	3	115,472
43300	Sherman-Denison, TX Metro Area	0.1	43.55%	0	23.50%	0.00%	0	5	121,145
43340	Shreveport-Bossier City, LA	0.3	37.21%	0	23.40%	0.00%	0	5	399,799

	Metro Area								
43580	Sioux City, IA-NE-SD Metro Area	0.1	48.61%	0	27.50%	0.00%	0	3	143,882
43620	Sioux Falls, SD Metro Area	0.3	37.13%	811	35.80%	96.55%	0	3	229,360
43780	South Bend-Mishawaka, IN-MI Metro Area	0.3	42.04%	97850	29.18%	59.00%	0	3	319,157
43900	Spartanburg, SC Metro Area	0.1	49.84%	0	26.12%	0.00%	0	5	284,713
44060	Spokane, WA Metro Area	0.5	36.18%	2694	31.92%	68.93%	6	3	472,147
44100	Springfield, IL Metro Area	0.2	28.28%	1347	35.82%	77.06%	0	4	210,390
44140	Springfield, MA Metro Area	0.3	35.77%	167116	34.34%	55.42%	0	3	693,141
44180	Springfield, MO Metro Area	0.2	37.04%	11244	30.00%	88.56%	0	4	435,175
44220	Springfield, OH Metro Area	0	39.83%	0	20.91%	0.00%	0	4	138,193
41060	St. Cloud, MN Metro Area	0.2	43.84%	3638	24.93%	32.63%	0	3	189,284
41140	St. Joseph, MO-KS Metro Area	0.1	45.10%	0	24.57%	0.00%	0	4	129,678
41180	St. Louis, MO-IL Metro Area	6.7	36.52%	711101	34.87%	67.23%	23.23	4	2,815,168
44300	State College, PA Metro Area	0.3	30.47%	753358	46.83%	66.72%	0	4	154,127
44700	Stockton, CA Metro Area	0.1	43.06%	5528	20.60%	44.81%	0	5	687,744
44940	Sumter, SC Metro Area	0	36.70%	0	18.74%	0.00%	0	5	107,570
45060	Syracuse, NY Metro Area	1.7	35.02%	97161	34.30%	63.95%	0	3	662,757
45220	Tallahassee, FL Metro Area	0.5	24.06%	220895	40.60%	71.28%	0	5	368,117
45300	Tampa-St. Petersburg-Clearwater, FL Metro Area	5.6	34.48%	309996	30.65%	72.14%	15.59	4	2,789,116
45460	Terre Haute, IN Metro Area	0.2	43.47%	4247	23.01%	31.13%	0	4	173,087
45500	Texarkana, TX-Texarkana, AR Metro Area	0	41.25%	0	19.64%	0.00%	0	5	136,252
45780	Toledo, OH Metro Area	0.3	40.84%	74532	28.86%	60.32%	0	3	651,020
45820	Topeka, KS Metro Area	0.1	35.90%	0	32.73%	0.00%	0	4	236,290

45940	Trenton-Ewing, NJ Metro Area	2	29.83%	203197	43.42%	64.35%	20	4	366,789
46060	Tucson, AZ Metro Area	3.3	31.17%	565292	32.39%	56.83%	16.2	5	982,154
46140	Tulsa, OK Metro Area	1.3	41.79%	12525	28.69%	49.01%	0	5	939,345
46220	Tuscaloosa, AL Metro Area	0.1	40.81%	36508	29.69%	71.03%	0	5	219,785
46340	Tyler, TX Metro Area	0.2	37.28%	3078	25.87%	94.77%	0	5	210,512
46540	Utica-Rome, NY Metro Area	0.4	34.39%	1344	27.80%	43.82%	0	4	299,347
46660	Valdosta, GA Metro Area	0	37.89%	0	23.66%	0.00%	0	5	137,657
46700	Vallejo-Fairfield, CA Metro Area	0.2	36.69%	681618	24.55%	51.84%	0	5	414,305
47020	Victoria, TX Metro Area	0.1	47.53%	0	17.35%	0.00%	0	5	115,396
47220	Vineland-Millville-Bridgeton, NJ Metro Area	0	40.43%	0	17.61%	0.00%	0	4	157,149
47260	Virginia Beach-Norfolk-Newport News, VA-NC Metro Area	2.8	34.06%	180496	32.03%	57.82%	0.22	5	1,675,343
47300	Visalia-Porterville, CA Metro Area	0	52.95%	0	14.08%	0.00%	0	5	443,688
47380	Waco, TX Metro Area	0.3	38.58%	11427	25.63%	42.75%	0	5	236,028
47580	Warner Robins, GA Metro Area	0.4	33.28%	0	23.98%	0.00%	0	5	140,713
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	41.8	22.90%	1005671	50.44%	71.97%	582.27	4	5,610,082
47940	Waterloo-Cedar Falls, IA Metro Area	0.1	45.84%	2160	29.56%	62.13%	0	3	165,095
48140	Wausau, WI Metro Area	0.1	51.51%	0	22.48%	0.00%	0	3	134,104
48300	Wenatchee-East Wenatchee,	0.1	49.31%	0	18.44%	0.00%	0	3	111,324

	WA Metro Area								
48540	Wheeling, WV-OH Metro Area	0	36.85%	7632	25.15%	98.41%	0	4	147,854
48660	Wichita Falls, TX Metro Area	0.3	45.43%	171	22.75%	11.11%	0	5	622,367
48620	Wichita, KS Metro Area	10.3	39.04%	65988	31.69%	33.92%	0	4	152,209
48700	Williamsport, PA Metro Area	0.1	45.04%	0	20.73%	0.00%	0	4	116,143
48900	Wilmington, NC Metro Area	0.5	38.21%	16423	35.52%	70.16%	0	5	363,766
49020	Winchester, VA-WV Metro Area	0.1	41.30%	0	25.60%	0.00%	0	4	128,757
49180	Winston-Salem, NC Metro Area	0.2	40.14%	201204	31.63%	80.87%	5.47	5	478,432
49340	Worcester, MA Metro Area	1.9	37.95%	226240	38.94%	72.98%	12.3	3	799,553
49420	Yakima, WA Metro Area	0	52.65%	0	16.72%	0.00%	0	3	244,485
49620	York-Hanover, PA Metro Area	0.3	46.17%	0	25.58%	0.00%	0	4	435,490
49660	Youngstown-Warren-Boardman, OH-PA Metro Area	0.2	42.13%	2081	24.73%	88.37%	0	3	564,804
49700	Yuba City, CA Metro Area	0	46.95%	0	18.12%	0.00%	0	5	167,194
49740	Yuma, AZ Metro Area	0	36.79%	0	17.37%	0.00%	0	5	196,509

7.2.2 Data for the China Group

City	High-tech Industry Employment Rate	Traditional Industry Employment Rate	Number of Academic Institute	High Education Rate	Intensity of Government support	Money Managed by VC	Comfort Score	Total Population
Anshan	2.98%	65.09%	3	11.00%	20.99%	18000	3	147.24

Anyang	1.83%	63.44%	3	4.72%	15.89%	0	5	107.53
Baiyin	1.69%	65.08%	0	4.49%	38.00%	0	4	49.66
Banbu	5.71%	47.99%	5	4.01%	22.98%	0	5	92.52
Baoding	4.52%	63.53%	12	4.81%	21.73%	0	4	106.25
Baoji	3.12%	64.67%	3	8.68%	60.81%	0	4	141.37
Baotou	4.46%	55.97%	9	7.42%	15.76%	0	3	141.48
Beijing	13.18%	39.08%	88	28.12%	52.27%	13787240	4	1174.63
Changchun	7.38%	50.07%	26	7.57%	31.45%	88080	3	362.32
Changsha	6.52%	47.09%	35	6.51%	15.93%	58000	5	240.95
Changzhou	3.55%	56.61%	9	7.04%	12.88%	100	5	226.67
Chengdu	6.03%	61.62%	31	4.35%	48.69%	44300	5	520.86
Chongqing	3.73%	59.87%	50	4.24%	19.27%	22598	5	1542.77
Daqing	12.34%	58.23%	6	5.97%	37.57%	3796	3	132.53
Dlian	4.30%	61.30%	31	11.00%	20.99%	42600	3	302.01
Dongguan	1.94%	43.96%	5	7.04%	8.77%	0	5	178.73
Foshan	3.08%	57.28%	3	7.04%	8.77%	4000	5	367.63
Fuzhou	5.95%	51.09%	30	5.86%	10.82%	10100	5	187.33
Guangzhou	5.14%	57.36%	-	7.04%	8.77%	264420	5	654.68
Guilin	5.69%	43.40%	8	3.29%	24.11%	0	5	75.79
Guiyang	4.66%	56.63%	24	3.50%	21.00%	4600	4	218.79
Haikou	4.50%	44.05%	10	5.77%	54.52%	3200	4	158.24
Hangzhou	5.80%	64.07%	35	9.53%	9.18%	293565	5	429.44
Harbin	4.51%	62.71%	46	5.97%	37.57%	135000	3	474.7
Hefei	6.17%	54.96%	43	4.01%	22.98%	259000	5	208.58
Huizhou	0.89%	81.88%	1	7.04%	8.77%	0	5	129.02
Jiangmen	1.95%	66.50%	3	7.04%	8.77%	0	5	137.57
Jilin	2.26%	50.63%	8	7.57%	31.45%	0	3	185.07
Jinan	4.10%	56.08%	65	5.47%	8.64%	159400	4	348.24

Jingdezhen	3.79%	61.96%	3	6.39%	22.31%	0	5	45.79
Jining	1.92%	49.74%	3	5.47%	8.64%	0	4	119.61
Kunming	6.68%	54.59%	24	3.51%	42.86%	5100	5	250.24
Lanzhou	7.16%	52.14%	25	4.49%	38.00%	27000	4	210.47
Liaoyang	2.85%	56.92%	4	11.00%	20.99%	0	3	72.7
Linyi	1.99%	57.38%	3	5.47%	8.64%	0	4	199.46
Liuzhou	2.91%	59.64%	7	3.29%	24.11%	0	5	103.83
Luoyang	7.37%	56.08%	3	4.72%	15.89%	1000	5	160.07
Mianyang	10.82%	55.22%	11	4.35%	48.69%	22000	5	122.31
Nanchang	3.99%	61.23%	44	6.39%	22.31%	17900	5	222.5
Nanjing	4.56%	60.19%	52	7.04%	12.88%	230500	5	545.97
Nanning	5.85%	49.46%	30	3.29%	24.11%	0	5	267.14
Nanyang	3.93%	57.91%	4	4.72%	15.89%	0	5	185.32
Ningbo	2.14%	69.48%	15	9.53%	9.18%	112580	5	221.83
Qingdao	2.48%	66.16%	25	5.47%	8.64%	13000	4	275.47
Qiqihar	3.71%	60.48%	5	5.97%	37.57%	0	3	141.99
Shanghai	7.17%	55.80%	66	22.66%	26.67%	10035720	5	1331.68
Shaoxing	2.03%	80.41%	7	9.53%	9.18%	0	5	64.9
Shenyang	5.31%	55.08%	40	11.00%	20.99%	35100	3	512.23
Shenzhen	3.92%	65.23%	8	7.04%	8.77%	3097420	5	245.96
Shijiazhuang	5.25%	54.81%	39	4.81%	21.73%	23000	4	242.78
Suzhou	1.87%	75.65%	12	7.04%	12.88%	249900	5	240.21
Taiyuan	5.30%	62.91%	36	7.20%	16.98%	29700	4	285.16
Taizhou	3.39%	57.59%	3	7.04%	12.88%	0	5	82.07
Tangshan	1.52%	67.29%	8	4.81%	21.73%	0	4	307
Tianjing	4.26%	59.65%	55	15.46%	18.13%	605286	4	802.9
Weifang	2.06%	61.71%	8	5.47%	8.64%	5000	4	181.25
Weihai	0.75%	74.61%	5	5.47%	8.64%	0	4	64.54

Weinan	3.83%	51.67%	1	8.68%	60.81%	0	4	96.8
Wuhan	5.55%	61.65%	63	8.08%	26.13%	312550	5	514.97
Wuhu	2.14%	67.91%	10	4.01%	22.98%	0	5	104.92
Wulumuqi	5.21%	52.43%	18	9.70%	28.80%	37236	4	231.88
Wuxi	3.08%	66.45%	10	7.04%	12.88%	50000	5	238.12
Xiamen	1.73%	75.55%	17	5.86%	10.82%	25200	5	177
Xian	10.09%	53.47%	47	8.68%	60.81%	441600	4	561.58
Xiangtan	2.00%	69.36%	9	6.51%	15.93%	0	5	87.75
Xiangyang	5.30%	48.41%	4	8.08%	26.13%	3000	5	221.75
Xianyang	4.93%	52.00%	13	8.68%	60.81%	0	4	89.7
Xining	7.11%	48.80%	9	7.47%	28.38%	0	4	114.13
Xinyu	1.79%	59.93%	1	6.39%	22.31%	0	5	92.24
Yantai	1.66%	69.70%	8	5.47%	8.64%	0	4	179.24
Yichang	3.65%	55.87%	5	8.08%	26.13%	0	5	124.79
Yinchuan	5.37%	46.77%	11	7.65%	23.35%	0	4	91.42
Yingkou	3.11%	51.31%	2	11.00%	20.99%	0	3	89.28
Yiyang	2.58%	39.04%	4	6.51%	15.93%	0	5	132.73
Zhaoqing	2.71%	64.81%	4	7.04%	8.77%	0	5	53.19
Zhengzhou	5.46%	51.03%	31	4.72%	15.89%	58300	5	285.01
Zhongshan	1.69%	64.22%	5	7.04%	8.77%	0	5	147.86
Zhuhai	2.02%	76.08%	10	7.04%	8.77%	0	5	102.65
Zhuzhou	3.84%	62.31%	9	6.51%	15.93%	0	5	100.21
Zibo	1.22%	68.78%	8	5.47%	8.64%	13000	4	278.77
Zigong	2.30%	59.65%	2	4.35%	48.69%	0	5	150.58

