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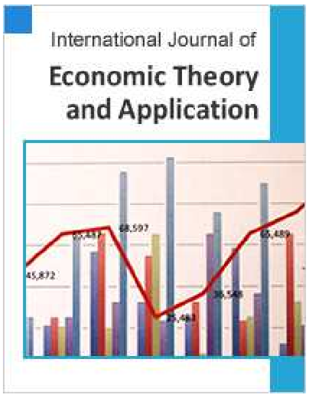

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Impact of Foreign Equity on Innovation and Performance of Listed High-Tech Companies Within and Outside Clusters in China

Tao Qu[1], Hang Xiang[2], Yan Qu[3]

[1]School of Economics and Trade, Guangdong University of Finance and Economics, Senior Research Personnel of National Economic Research Center, Guangzhou, Guangdong, China
[2]Construction Fourth Engineering Division Corp, Guangzhou, Guangdong, China
[3]Department of Finance and Economics, Guangdong Engineering Polytechnic Institute, Guangzhou, Guangdong, China

Email address
qutao1971@yahoo.com (Tao Qu), qutaokathy@163.com (Tao Qu)

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Abstract
Based on the data of 188 GEM-listed companies until 2012, this paper uses principal component regression analysis to compare disparities in creative, learning and factor input capacities by dividing samples into a cluster group and a non-cluster group. The results indicate that companies within clusters easily access government supports, attach importance to learning effects, demonstrate greater capabilities to absorb skills and know-how spilled over from foreign investment companies, and experience less impact due to crowd-out effects caused by foreign capital. Endogenous creation within clusters with little contribution to performance implies that superiority of resource agglomeration and learning networks have not converted into creative superiority. Companies outside clusters place greater emphasis on exogenous innovation driven by foreign capitals than do companies within clusters. We propose that, lacking capital and technical stock, governors should pay more attention to exogenous creative sources, accelerate the industrialization process of creative achievements through training and technical exchange and establish technical service platforms.

1. Introduction

In China, numerous clusters have emerged and fostered by preferential policies in land, tax exemption under Regional Economic Strategy since the promulgation of the Twelfth Five-year Plan to develop National Strategic Emerging Industries by the State Council in 2012. Local governors have established industrial and high-tech parks to attract foreign capital and have built industrial chain associations to stimulate technique transfer and spillover and to upgrade traditional industries. The development of the regional economy highly depends on FDI efficiency spillovers and cluster innovation.

Chinese clusters experience three procedures: spontaneous agglomeration, national planning and innovation upgrades.

Spontaneous agglomeration happened ever sins the end of 1970s till 1989, which are consisted of manual mills and small and medium enterprises focus on manufacturing of handicrafts, assembling of parts and creating of clothing textiles. For example, maker-agglomeration of small objects in Yiwu and Zhejiang and the toy industry cluster in

Salt City of Jiangsu, nature by endogenous innovation, near geographic location and affinity. Through over ten years of fast growth, along with economic globalization and advanced science and technology, problems like poor processing quality, small scaled production and weak innovative ability spontaneously emerged in native-born clusters.

In 1979, the State Council promulgated Sino-Foreign Joint Venture Enterprise Law, the first regulation on FDIs. Four special economic zones, say, Shenzhen, Shantou, Zhuhai and Xiamen are permitted to established. In the following 10 years, capital rapidly flowed into the Chinese mainland on small scale, with \$25 billion of actual utilization inflows and \$2.09 billion of average annual inflows, mainly from Hong Kong and Macao, with labor-intensive focus.

National planning play roles in 1990-2006. Systematic reform of science and technology was published by the Central Committee of the CCP and the State Council (1985) and tested in crucial development areas, by adopting special preferential policies and formation of industrial development zones. By 1988, the National Torch Plan to construct and expand hi-tech innovative park and to maximize productive forces resulted from scientific and technological achievement conversion was implemented. This served as the prelude to the construction of high-tech zones throughout the country. Science and technology parks became extensions of the SCEZ (special economic zone) economy and windows towards foreign affairs. Open markets, induced capital, updated transformation of traditional clusters come into being in this period. Science and technology parks, such as Zhongguancun Science Park in Beijing, Pudong New Area in Shanghai and Zhongshan Torch Development Zone in Guangdong, were built in succession with strong support of funds, policies and projects provided by central and local governments.

In 1992, Comrade Deng Xiaoping announced China will open markets toward the world on his southern patrol. Which fostered inward FDI reached \$11 billion. The actual utilized value of foreign capital initially exceeded overseas borrowing. The average annual inward capital reached \$37.02 billion at yearly growth of 36.20% in 1990-2006. Industrial concentration, cheap labor and land preferential policies were main courses for attracting foreign investment. Within 15 years, major economic indicator increased by over 50% in 53 national hi-tech parks, contributed to the prosperity of the regional economy, increased operating income by over 393 times from CNY8.73 billion to CNY3.44 trillion, and exports by over 619 times from USD180 million to USD111.65 billion, and payable taxes and fees by over 414 times reaching CNY161.58 billion.

Ever since 2007, transition emerged from traditional industrial clusters towards innovation-driven clusters. Some hi-tech parks are capable to create and establish affiliate and necessary supportive systems. By the end of 2012, 105 state-level hi-tech zones had accumulated 980 thousand scientific and technological personnel, wherein 90 thousand or more are MDs and nearly 20 thousand are PhDs, ten thousand were from overseas. Of the 7 million employees, one-third have secondary degrees or above. There are batches of post-doctoral research stations, more than 400 hi-tech business service centers, and thousands of supportive servicing institutions within clusters, shaping a complete and systematic pool of R&D-incubation-industrialization of technological achievements. R&D expenses occupies one-fifth of aggregate costs of national R&D activities, and R&D expenses per capita on cluster bases are 6 times on national basis. Authorized invention patents occupy 50 percent of the national patents.

Meanwhile, with respect to rising costs associated with the work-force and materials, foreign investors transfer to Cambodia, the Philippines, Vietnam and other southeast Asian economies with lower labor force costs, resulting slow or even negative growth in real use of foreign capitals in China. The shift in strategy from "investment promotion" to "investment selection " is imminent, though it gives rise to two key strategic problems. The first problem is whether an innovation element can be the cause or reason for foreign direct investment. The second concern involves the relationship between foreign ownership drive cluster innovation and business performance.

Based on principle composition analysis, this article compares the contribution of innovative factors, such as foreign equity, talents, education level, R&D investment and government support of high-tech entities within and outside clusters sampled by GEM listed companies, as it examines the following three issues. (1) The first concern is cluster innovation and foreign equity, which may become dependent routes for the development of high-tech entities. (2) The second issue is whether the existing cluster innovation acquires know-how mainly due to its endogenous nature, that is, through FDI spillovers with a high dependence on foreign capital, or due to its exogenous nature, which is based on local capital and techniques that are highly dependent on independent research and development. (3) The third issue is whether foreign equity within clusters first plays a direct role on performance or on creative capacity, which indirectly impacts operation performance. In section two, we review previous literature with the aim of distinctly defining innovation-driven cluster. In section three, we shape the development stages and explain the situation of clusters in China. Sections four and five present our data sources, model choice, empirical tests and results. In the final section, we present our conclusion and offer policy suggestions.

2. Literature Review

2.1. Cognition of Innovation Driven Clusters

In 2001, the Ministry of Science and Technology put forward the strategy of the "second innovation" by expanding the national high-tech zone to improve industrial clusters and foster innovation. Innovation-driven clusters became the key means in regional innovation to upgrade existing industrial clusters into high-end centers. Innovation-driven clusters are vital for attracting foreign direct investments (FDIs) and promoting FDI efficiency spillovers through the convergence of creation-related resources. This gives rise to several questions, however. What roles do foreign equities play in existing cluster creation activities? Is the channel to stimulate FDI efficiency spillovers in clusters to drive business performance direct or facilitative? What are the critical principles for identifying the significance of locations characterized by clusters upon consequences of FDI efficiency spillover.

Mytelka (2003) argues that innovative clusters are consistent with Porter's defined informal clusters, which, as the highest type of cluster, exhibit a highly developed nature. Xiao (2003) defines innovation-driven clusters as chains formed by know-how centers consisting of customers, suppliers, universities, intermediary organizations and other knowledge-intensive services. Luo et. al (2003) regard innovation-driven clusters as wonderful platforms for the cultivation of creation, and as an existence mode of innovation as they provide innovative individuals with demand enforcement, survival paradigms and resource supports. Li lin (2004) defines an innovation-driven cluster as a regional network formed by a group of common and complementary innovative enterprises and associated institutions rooted in a certain area within one specific industry and comprised of a relatively stable system based on formal or informal long-term cooperations and exchanges among enterprises, universities, local governments, scientific research institutes and other institutions or individuals. Based on this, Li pong (2012) concludes that innovation-driven clusters as technical and economic networks are characterized by an agglomerative economy and knowledge outflow that constantly drive clusters towards the global high-end chain.

Drawing from the above definitions, we define innovation-driven clusters as advanced forms of clusters that focus on creation and emphasize interactions and knowledge flows across innovative subjects characterized by a high degree of trust and industrial links between entities that foster cooperation and competition within clusters. Cluster enterprises have the capacity to continuously innovate based on resources, including know-how and techniques, and lead the whole cluster to integrate into the global high-end value chain.

2.2. Relationships Among Fdi Efficiency Spillover, Cluster and Performance

There are three academic views on relationships among FDI spillover, cluster and business performance. One is the positive view. Cooke et al. (1985) posit that an agglomerative economy, institutional learning, joint management, proximity capital and interactive creation are vital to the generation, diffusion, application and development of knowledge. The agglomeration economic theory represented by Porter argues that scaled economies, positive externalities and scope economy generated by clusters bring about external advantages characterized by efficiency spillovers for industries. Nachum et. al (2003) compare cluster and non-cluster groups and find that cluster innovation networks contribute more to business performance. Djankov et al. (2000) show that foreign capital positively improved the total factor productivity in the Czech Republic and Slovakia. Yao et.al (2007) confirm that FDIs bring advanced management skill and production technology to new industrial economies, which is conducive to elevated industrial efficiency and local productivity. Qu et al. (2013) verify that local absorptive capacity determines the magnitude of the role of FDI on local innovative achievement. Qu (2012) compares cluster and non-cluster enterprises and finds that a cluster network facilitates the establishment of close and exoteric contacts among cluster entities, thereby enhancing the learning abilities and improving business performances of the cluster entities. The second view contends that FDI spillovers are conditionally generated. Blomstrom and Kokko (2000) suggest that the ability of domestic companies to absorb FDI technology spillover depends on indigenous know-how stock. Linda (2007) argues that in the financial sector, FDIs can speed up the economic growth of the host country on the premise of perfect information transfer, technical progress and venture management. Based on manufacturing data of OECD nations, Ramasamy and Yeung (2010) confirm that foreign capital agglomeration is more important than market size and human capital in the host country. Tanaka et al. (2012) find that in the delta of the Yangtze River of China, FDIs assume a positive role on local business performances, and more significantly promote development of entities in near proximity over a longer distance. Gugler and Brunner (2007) believe that clusters exert an important influence on the capacity to absorb FDI technology spillovers. The third is a negative view. Grabber (1993) argues that, for value-added segments in innovation, design and research and development concentrate in the home office, foreign enterprises in clusters are created with low technical content, engaged with poor autonomy and poor relationships with the host markets, businesses and consumers. Furthermore, this view purports that FDI devote less to upgrade of local technologies.

Few studies have focused on the impacts of FDI efficiency spillovers on business performance according to the profiles of innovation-driven clusters. Furthermore, academic conclusions on relationship among FDI spillover, clusters and performance are not consistent, though FDIs are found to affect the production modes and market statuses of cluster enterprises through the cluster network. Cluster enterprises establish up-and down-stream industrial links with multinational entities and acquire FDI efficiency spillovers by demonstration-and-imitation effect, thereby upgrading techniques and management skills and shaping complementary advantages. Based on data analyses of high-end new technology enterprises in Zhongguancun Science Park in 2002-2003, Sue and Zhou (2008) propose that the dynamic evolution of the cluster ecosystem affects the perception of the cluster enterprise on surroundings, which will eventually affect their innovation decision making. Yang et al. (2007) study the Tianjin Binhai New Area and consider clusters as models of regional innovation and posit that cost-effective clusters with complete and agglomerated supporting industries can attract FDIs and further upgrade clusters through the role of FDI technology spillovers and managerial demonstration. Accordingly, clusters and FDI spillovers are effective paths to realizing regional innovation. Therefore, the effects and channels of FDI spillovers in existing Chinese clusters require further examination.

3. Model and Data Sources

To further study the impact of FDI efficiency spillover on cluster innovation and business performance, we use principle component analysis on samples of GEM companies listed before March of 2012. We then compare innovation factors within or beyond clusters and their contributions to business operations to identify key influencing factors that determine whether existing clusters are of the exogenous or endogenous type and that impact the FDI technique spillover on the micro-operation of enterprises.

3.1. Theory of Principle Component Analysis

Principle component analysis is a dimension reduction statistical analysis method that lessens original multiple indices to fewer main comprehensive indices, and it is generally employed to study complex system-embracing multi-factors. Too many variables increase the difficulty and complexity of the analysis. Utilizing correlations among original variables, we have fewer new variables than the original, and we extract the main comprehensive variables to measure, thus retaining more of the original information and simplifying the problem.

Assume we have original samples n and each sample has p variables, which constitute the matrix of n*p:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

We record the original variable indicator as $x_1, x_2, \ldots, x_p$, and measure new comprehensive variables after a dimension reduction for the $z_1, z_2, z_3, \ldots, z_m (m \le p)$. The coefficient l_{ij} is determined as follows:

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ z_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \quad\cdots\cdots\cdots\cdots \\ z_m = l_{m1}x_1 + l_{m2}x_2 + \cdots + l_{mp}x_p \end{cases}$$

Z_i and $z_j (i \neq j; I, j=1, 2, \ldots, m)$ are independent of each other. The variance of z_1 is the maximum among the linear combination of $x_1, x_2, \ldots$ and x_P. The variance of z_2 is the maximum among the linear combination of $x_1, x_2, \ldots, x_P$, irrelevant of z_1. The variance of z_m is the maximum among the linear combination of $x_1, x_2, \ldots, x_P$, irrelevant of $z_1, z_2, \ldots\ldots, z_{m-1}$.

The new aggregative indicator $z_1, z_2, \ldots, z_m$ is termed separately as the 1st, 2nd,…, mth main composition of the original index $x_1, x_2, \ldots, x_P$.

To summarize, the essence of principle composition analysis is to obtain loads $z_i(i=1, 2, \ldots, m)$, which proved in mathematics to be eigenvectors corresponding to the m eigenvalue of the correlation matrix of original variables $x_j(j=1, 2, \ldots, p)$ for each principle component l_{ij} ($i=1, 2, \ldots, m$; $J=1, 2, \ldots, p$).

3.2. Calculation Steps of Principle Composition Analysis

3.2.1. Calculating Correlation Coefficient Matrix

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \vdots & & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix}$$

r_{ij} (i, j=1, 2, …, p) are the correlation coefficients of the original index x_i and x_j ($r_{ij}=r_{ji}$), with the formula of computation as follows:

$$r_{ij} = \frac{\sum_{k=1}^{n}(x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)}{\sqrt{\sum_{k=1}^{n}(x_{ki} - \bar{x}_i)^2 \sum_{k=1}^{n}(x_{kj} - \bar{x}_j)^2}}$$

3.2.2. Calculating Eigenvalues and Eigenvectors

To solve the secular equation $|R - \lambda i| = 0$, we generally use the Jacobi method to find the p latent root λ_g, therein g=1,2,3,…,p. Sorted by the size of the latent roots, we obtain $\lambda_1 \ge \lambda_2 \ge \lambda_3 \ldots\ldots \ge \lambda_p \ge 0$, demanding $\sum_{j=1}^{p} e_{ij}^2 = 1$, in which e_{ij} represents the jth component of the eigenvector e_i.

3.2.3. Calculating Contribution Rate and Accumulative Contribution Rate of Pricincple Composition

The contribution rate is calculated according to the following formula:

$$\frac{\lambda_i}{\sum_{k=1}^{p} \lambda_k} \quad (i = 1, 2, \cdots, p)$$

The accumulative contribution rate is calculated according to following formula:

$$\frac{\sum_{k=1}^{i} \lambda_k}{\sum_{k=1}^{p} \lambda_k} \quad (i = 1, 2, \cdots, p)$$

Generally, we take eigenvalues above 80% of the accumulative contribution and where $\lambda_1, \lambda_2, \cdots, \lambda_m$ over 1 of the latent root correspond to the 1st, 2nd,…, mth (m ≤ p) principle composition.

3.2.4. Calculating Loads of Pricinciple Comosition

$$l_{ij} = p(z_i, x_j) = \sqrt{\lambda_i} e_{ij} (i, j = 1, 2, \cdots, p)$$

3.3. Systematic Evaluations

After determining the number of principle compositions, we take the principle composition for systematic evaluation. First, we calculate the linear weighted value of each principle composition as per formula:

$$F_{ig} = \sum_{j=1}^{p} l_{gj} r_{ij} \tag{1}$$

$$i = 1, 2, 3, ..., n$$
$$j, g = 1, 2, ..., p$$

We then draw comprehensive value F_i by summing up the k principle composition weighted by the contribution rate of each where $d_g = \lambda_g / \sum_{g=1}^{p} \lambda_g$. The basic formula is as given below:

$$F_i = \sum_{g=1}^{k} d_g \cdot F_{ig} \tag{2}$$

$$i = 1, 2, 3, ..., n$$
$$j, g = 1, 2, ..., k$$

Finally, we linearly regress using the least square method on k units of F_i, thus determining the devotion size and direction of innovation factors on business performance.

3.4. Sample Selection and Data Sources

Research indicates that an innovation-driving cluster is an important index as it reflects learning and creation ability. Therefore, we should reevaluate the role of FDIs on business performance from the profiles of this type of cluster. Regarding clusters as a vital location condition, does the FDI efficiency spillover directly impact business performance or indirectly impact innovation capacity through influence on? To answer this question, we use group studies based on samples of GEM listed companies prior to February 2012. Data are derived from the CSMAR database and annual financial reports released by enterprises. The GEM is the second-board stock market relative to the main market. It refers, in particular, to Shenzhen GEM, which is designed to support small- and medium-sized enterprises (SMEs), especially high-growth science and technology companies (ST firms) and to build legal exit mechanisms and financing platforms for venture capital firms (VC firms) and risk investments as incubators of high-growth ST firms. China established industrial parks, high-end new science and technology parks and economic development zones to attract industrial agglomerations, which we regard as innovation-driven clusters in subsequent studies, in favor of self-dependent innovations. Considering data completeness and financial stability, we classify companies with business address located in industrial parks, economic development zones, high-end and new science and technology parks into the cluster group and companies with business addresses located in other places into the non-cluster group. ST and PT companies are eliminated due to their abnormal financial situation. Thus, we have 188 high-tech listed companies, 102 in the cluster group and 66 in the non-cluster group.

We use performance (y) to reflect ability of operation and commercialization, which considers creation and external and internal learning results. We measure creation performance by patent authorized numbers (x_1), external learning ability by government subsidies (x_2) and foreign equity ratio (x_3), thus reflecting promotional ability by absorbing knowledge and skills spilled over through FDIs and government supports beyond enterprises. Internal learning ability is reflected by technical staff proportion (x_4), R&D expenditure per capita (x_5), education index (x_6) and diversification of education (x_7), which represent contributions of internal ST talents, devoted private capital, education degree and complementary talents to ascended ability. Variable definitions and economic implications are shown in table 1.

Table 1. *Systematic evaluation indicators of innovation abilities in high-tech enterprises.*

Level-1 indicators	Level-2 indicators	Level-3 indicators	Definition of Level-3 indicators
Commercial ability	Performance level	Sales(y) Sales per capita	Sales of products or services. Sales as percentage of number of employees.
Productive capability of innovation	Innovation performance	Number of authorized patents (x_1)	Number of authorized patents within the period, reflecting innovation performance.
External learning capabilities	Ability to acquire external know-how via official supports	Government grants(x_2)	Special funds supported by State Ministry of Science and Technology, Science and Technology Bureau and the local government; scientific research award fund for innovation team supported by Organizational Department of Municipal Committee.
	Ability to acquire external know-how via attracting foreign capitals	Ratio of foreign equity (x_3)	Proportion of foreign equity in company shares.

Level-1 indicators	Level-2 indicators	Level-3 indicators	Definition of Level-3 indicators
Internal learning abilities	Internal knowledge stock	Ratio of technical staff(x_4)	Technical staff as percentage of total employees.
	R & D intensity	R&D expenditure per capita (x_5)	R&D expenditure divided by number of employees.
	Employee level of education	Education index (x_6)	Undergraduate, graduate, master and doctoral education postponed for 2 years, 5 years, 8 years and 11 years, respectively, at a benchmark of 3 years of professional education. Education index calculated as per formula: percentage of staff with vocational education X3+ percentage of staff with bachelor degree X5+ percentage of staff with master degree X8+ percentage of staff with doctoral degree X11.
	Employee complementary knowledge	Educational diversification(x_7)	Ordinal variables. If 100% of the company's employees have bachelor's degree, 1 point; if 50% of employees have bachelor's degree, 50% have master's degree, 2 points; if 30% of employees have vocational degree, 40% have bachelor's degree, 20% have master's degree, and 10% have doctoral degree, 4 points.
Nature of Companies	Business experience	Age of companies	Business period since the establishment of companies.
	Size	Companies' assets	Companies' total assets.

4. Model Test and Results Analysis

4.1. Descriptive Statistics

Table 2. *Variable descriptive statistics.*

Indicators	Mean Value			Standard Deviation		
	Total sample(N=188)	Non-cluster group sample(N=66)	Cluster group sample(N=102)	Total sample (N=188)	Non-cluster group sample (N=66)	Cluster group sample (N=102)
Companies' Total Assets (Ten thousand yuan)	104,733.18	104,632.22	105,053.45	673.21	642.01	614.04
Sales(ten thousand yuan)	42,562.79	42,506.93	42,579.15	417.01	445.24	497.15
Sales per capita (ten thousand yuan per person)	5,277.04	5,270.40	5,280.50	82.32	18.26	73.00
Number of authorized patents (x_1)	8.68	8.95	8.45	9.85	12.00	13.00
Government grants(ten thousand yuan) (x_2)	722.13	723.27	725.11	77.24	22.74	78.00
Ratio of foreign equity (x_3)	3.74	3.68	3.76	10.71	10.44	10.50
Ratio of technical staff (x_4)	24.11	22.47	26.47	24.32	31.75	25.90
R&D expenditure per capita (ten thousand yuan per person)(x_5)	3.39	3.37	3.44	3.46	3.48	3.90
Education index (x_6)	1.63	1.64	1.65	0.74	0.77	0.74
Educational diversification (x_7)	2.18	2.17	2.18	0.44	0.43	0.44
Age of companies	10.79	10.80	10.78	8.35	6.35	8.37

Comparing 11 indicators of samples, we find most are similar. The mean values of nine indicator in clusters are higher than those in non-clusters, for example, total assets (105053.45 to 104632.22), sales (42579.15 to 42506.93), sales per capita (5280.50 to 5270.40), government grants (725.11 to 723.27), ratio of foreign equity (3.76 to 3.68), ratio of technical staff (26.47/22.47), R&D expenditure per capita (3.44 to 3.37), education index (1.65 to 1.64), educational diversification (2.18 to 2.17). These results suggest that cluster companies have certain advantages in performance as well as internal and external learning abilities. Additionally, talent is essential to high-tech oriented cluster enterprises, with 20 percent of technical staff in excess with respective to companies beyond clusters. While most cluster enterprises are new (10.78 to 10.80), the number of authorized patents is less than it is for entities in the non-cluster group (8.45 to 8.95).

The cluster group also has a greater standard deviation in government grants (78 to 22.74), sales per capita (73 to 18.26) and age of companies (8.37 to 6.35) than non-cluster group, thus indicating that cluster enterprises are eligible for government grants diversely and with great disparities in creation times and sales performances. Cluster enterprises also demonstrate the largest gap in technical staff proportion (31.75 to 25.90) compared to non-cluster enterprises (see Table 2).

4.2. Factor Analysis and Eigenroot Test

The variable correlation matrix shows, for cluster companies, that R&D expenditures per capita (x_5) are obvious and positive, while the technical staff proportion (x_4) and education index (x_6) are markedly and negatively correlated with government grants (x_2), thus suggesting an incentive function from government support for the creation of necessary R&D inputs. Official funds are only used for compensating capital shortages for creation, rather than for the introduction and cultivation of senior talent, which is contrary to the improvement of overall quality. The number of authorized patents(x_1)is significantly and positively related to government grants(x_2)and education index(x_6), indicating that staff quality and government support may stimulate creative activities (see Table 3).

Table 3. *Correlation Matrix between Variables in the Cluster Group.*

	x_1	x_2	x_3	x_4	x_5	x_6
x_1	1.000					
x_2	0.299***	1.000				
x_3	0.071	-0.018	1.000			
x_4	-0.044	-0.155*	-0.069	1.000		
x_5	0.106	0.561***	-0.002	-0.041	1.000	
x_6	0.179**	-0.141*	-0.023	0.044	-0.109	1.000

Note: "***" represents significance at the 1% level using a one-tailed test; "**" represents significance at the 5% level using a one-tailed test; "*" represents significance at the 10% level using a one-tailed test.

Table 4. *Correlation Matrix between Variables in Non-cluster Group.*

	x_1	x_2	x_3	x_4	x_5	x_6
x_1	1.000					
x_2	0.023	1.000				
x_3	-0.041	0.012	1.000			
x_4	0.197*	0.254**	-0.040	1.000		
x_5	0.029	0.104	-0.089	-0.019	1.000	
x_6	-0.002	0.275**	0.168*	0.355**	-0.074	1.000

Note: "***" represents significance at the 1% level using a one-tailed test; "**" represents significance at the 5% level using a one-tailed test; "*" represents significance at the 10% level using a one-tailed test.

For companies beyond clusters, education index (x_6) and the ratio of technical staff (x_4)are obviously and positively correlated with government grants (x_2), implying that official funds are mainly used for training and talent introduction to improve overall quality. Education index (x_6) is significantly and positively correlated with the ratio of foreign equity (x_3) and ratio of technical staff (x_4), thus showing that inward foreign capital contributes to flow and the introduction of talented personnel to enhance the overall quality of employees. The number of licensed patents (x_1) and the ratio of technical staff (x_4) is obviously and positively correlated, thus suggesting that skilled labor force promotes innovation (see Table 4).

Table 5. *Total Variance Decomposition.*

Sample	Component	Total	Variance contribution rate(%)	Cumulative variance contribution rate(%)
	1	2.731	38.847	38.847
in cluster group	2	1.681	24.691	63.538
	3	1.562	21.705	86.243
	1	2.627	37.112	37.112
in non-cluster group	2	1.685	24.757	61.870
	3	1.530	21.171	84.040

Note: column "Total" corresponds to eigenroot of each component

Information drawn from relevant data may overlap for possible correlation between indices. We use SPSS17.0 software for principal component analysis to reduce data dimensions using the projection method and discompose information into discrete parts in the lower dimension to obtain a more meaningful interpretation. The eigenvalue of the three principal components and their variance contributions are shown in Table 5.

We extract the first three principle components in the cluster and non-cluster groups with eigenroots greater than 1 and list variance contributions from top to bottom, thus explaining 86.243% and 84.04% of the variance of original variables, respectively, and reflecting most of the information available for basic indicators. Therefore, we use these three principle components to replace variables corresponding to the original six tertiary indicators.

Table 6. *Results of KMD and Spherical Bartlett Test.*

Sample	KMO test	spherical Bartlett test	df	Sig.
in cluster group	0.492	56.869	15	0.000
In non-clustered group	0.513	19.564	10	0.034

For samples of clustered and non-clustered groups, KMO (Kaiser-Meyer-Olkin metrics) statistics are 0.492 and 0.513, respectively, and the Bartlett sphericity test reveal 0.000 and 0.034 for P values below 0.05 level of significance. Thus, we reject the null hypothesis that groups of data are suitable for factor analysis (see Table 6).

Table 7. *Factor Loading Matrix of Two Sample Groups.*

Matrix and sample groups	component matrix						rotated component matrix[a]					
	cluster group			non-cluster group			cluster group			non-cluster group		
components	1	2	3	1	2	3	1	2	3	1	2	3
x_1	0.450	0.699	0.007	0.246	0.464	-0.656	0.351	0.737	0.156	0.029	-0.023	0.840
x_2	0.886	-0.029	0.097	0.634	0.139	0.423	0.885	0.075	0.089	0.717	0.302	-0.081
x_3	0.051	0.167	-0.776	0.151	-0.693	0.057	-0.124	0.075	0.782	0.217	-0.543	-0.405
x_4	-0.276	0.025	0.615	0.753	0.185	-0.226	-0.150	0.071	-0.654	0.651	-0.045	0.476
x_5	0.790	-0.169	0.197	-0.015	0.585	0.600	0.828	-0.061	-0.042	0.092	0.823	-0.131
x_6	-0.197	0.797	0.181	0.750	-0.306	0.081	-0.257	0.789	-0.14	0.768	-0.266	-0.047

Note: (1) Extraction method: principal component analysis. (2) Rotation method: Kaiser standardized orthogonal rotation method. (3) a: converge after an iteration procedure.

There is no significant difference on partial loads of original variables. To conveniently name determinants, we rotate factor loadings. Table 8 indicates that the coefficients are divided after rotation. For the cluster group, the first principal components have greater loads on R&D expenditure per capita (x_5) and government grants (x_2), indicating these two variables are subject to innovation input indicators and are highly correlated. Thus, they are grouped into the 'input factor" category. The second principal component has larger loads on the education index (x_6) and authorized patent number (x_1) variables and thus belong to the innovation indicator as these two variables are highly correlated. Thus they are placed in the "innovation factor" category. The third principal component is highly correlated with the ratio of foreign equity (x_3) and the ratio of technical staff (x_4), which reflect learning ability. Thus, these two factors are placed in the "learning factor" category.

Table 8. *Principal Component Description of Two Sample Groups.*

Main ingredients	Highly relevant variables in cluster group		Highly relevant variables in non-cluster group		Implied meaning
Input factor	x_5	R&D expenditure per capita	x_5	R & D expenditures per capita	Reflect sources of innovation funds and degree of attention on creation.
	x_2	Government grants	x_3	Ratio of foreign equity	
Innovation factor	x_6	Education index	x_1	Number of authorized patents	Reflect innovation capability and achievements.
	x_1	Number of authorized patents			
Learning factor	x_4	Ratio of technical staff	x_2	Government grants	Reflect learning ability and channel
	x_3	Ratio of foreign equity	x_6	Education index	
			x_4	Ratio of technical staff	

For the non-cluster group, the first principal component has greater loads on education index (x_6), government grants (x_2) and ratio of technical staff(x_4)subject to learning ability index, indicating that these three variables are highly correlated and can be grouped into the "learning factor" category. The second principal component has larger loads on R&D expenditures per capita (x_5) and foreign ownership (x_3), which belongs to business input indicators, indicating that these two variables are highly correlated and are grouped into the "input factor" category. Similarly, the third principal component has a larger load on the number of authorized patents (x_1) subject to the innovation ability index and grouped into the "innovation factor" category.

Visual innovation capability of high-tech companies can be determined from the profiles of the inputs and the innovation and learning factors. The two sample groups vary in their maximum factor loadings. For the cluster enterprises, innovation inputs mainly depend on state support and enterprise-owned R&D expenditures, and staff's all-around quality determine innovation achievement mainly by attracting top talents and FDI technology spillovers to acquire knowledge. For enterprises beyond clusters, innovation inputs originate from self-owned R&D expenditures and inward foreign capitals. With respect to the introduction of top talents, state grants upgrade the overall quality of the staff through improved learning abilities (see Table 8).

4.3. Equation and Score of Principle Component

Table 9. Principal component score coefficient matrix of two sample groups.

Variable	Eigenvectors of cluster group			Eigenvectors of non-cluster group		
	F_1	F_2	F_3	F_1	F_2	F_3
x_1	0.34	0.64	0.01	0.12	-0.64	0.06
x_2	0.67	0.03	0.09	0.59	0.17	-0.22
x_3	0.04	0.15	-0.75	0.19	0.43	-0.65
x_4	-0.21	0.02	0.60	-0.01	0.54	0.59
x_5	0.60	-0.16	0.19	0.59	-0.28	0.08
x_6	-0.15	0.73	0.18	0.50	0.13	0.42

Table 9 presents the factor score matrix - un-rotating factor solution - from which we draw expressions of the main components for the cluster group. These include:

$$\begin{aligned} F_1 &= 0.34x_1 + 0.67x_2 + 0.04x_3 - 0.21x_4 + 0.6x_5 - 0.15x_6 \\ F_2 &= 0.64x_1 + 0.03x_2 + 0.15x_3 + 0.02x_4 - 0.16x_5 + 0.73x_6 \\ F_3 &= 0.01x_1 + 0.09x_2 - 0.75x_3 + 0.60x_4 + 0.19x_5 + 0.18x_6 \end{aligned} \tag{3}$$

Similarly, each primary component for the non-cluster group is expressed as:

$$\begin{aligned} F_1 &= 0.12x_1 + 0.59x_2 + 0.19x_3 - 0.01x_4 + 0.59x_5 + 0.5x_6 \\ F_2 &= -0.64x_1 + 0.17x_2 + 0.43x_3 + 0.54x_4 - 0.28x_5 + 0.13x_6 \\ F_3 &= 0.06x_1 - 0.22x_2 - 0.65x_3 + 0.59x_4 + 0.08x_5 + 0.42x_6 \end{aligned} \tag{4}$$

Taking a relative value or numerical value of variables, we calculate the variance contribution rate of the common factor weighted by the evaluation statistic:

$$F = \frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3}F_1 + \frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3}F_2 + \frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3}F_3 \tag{5}$$

Computing weights of each principal component of the cluster group samples, we have:

$$\frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3} = \frac{2.731}{2.731+1.681+1.562} = 0.4571$$

$$\frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3} = \frac{1.681}{2.731+1.681+1.562} = 0.2814$$

$$\frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3} = \frac{1.562}{2.731+1.681+1.562} = 0.2615$$

Similarly, the weights of each principal component of the non-cluster group samples are calculated as below:

$$\frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3} = \frac{2.627}{2.627+1.685+1.530} = 0.4497$$

$$\frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3} = \frac{1.685}{2.627+1.685+1.530} = 0.2884$$

$$\frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3} = \frac{1.530}{2.627+1.685+1.530} = 0.2619$$

According to formulas 1 and 2, we obtain a comprehensive score that evaluates innovation abilities of listed high-tech enterprises in the two groups. The results are shown in Table 10.

Ranking by principal component scores, we find that samples in the cluster group received larger scores for input and learning factor compared to samples in the non-cluster group, indicating that cluster enterprises prevail in capital attraction, emulation and evaluation. Comparing component weights of the two groups, we conclude that cluster enterprises focus more attention on capital and other input elements to enhance their learning ability. Companies in the cluster group received lower scores for innovative factor, thus explaining their weaker innovation capacity. Cluster strengths in resource agglomeration and learning networks have not yet been converted into innovation advantages.

Table 10. *Scores and ranks of principal components of each sample group.*

sub-sample	input factor	rank	innovation factor	rank	learning factor	rank	comprehensive	rank
cluster Group	7.50	1	1.44	2	5.58	1	6.74	1
non-cluster group	6.45	2	3.40	1	3.40	2	4.46	2

4.4. Regression Analysis on Principle Component

To further compare spillover effects of foreign equity by companies within and beyond clusters, we extracted three principal components F_1, F_2, F_3 as independent variables and sales (y) as the dependent variable for multiple linear regression analysis. From regressive results for the cluster group and the non-cluster group (see table 11), original decision coefficients were 0.947 and 0.984, and adjusted coefficients of determination were 0.918 and 0.952, respectively, indicating a good fitness of the model. For the two models, the Durbin-Watson values are 2.124 and 1.825, respectively. $d_l = 0.96$, $d_u = 1.63$, $d_u < DW < 4 - d_u$ indicate that no autocorrelation exists for the two models at the 5% significance level.

Table 11. *Regressive Results on Principal component.*

	Cluster Group(n=102)		Non-cluster group (n=86)	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**
Constant	10.33*** (87.277)	0.028	10.472*** (101.44)	0.074
F_1	1.25*** (15.038)	0.001	-0.45*** (-6.06)	0.075
F_2	-0.91** (-8.182)	0.011	0.085*** (0.1)	0.075
F_3	-1.10** (-10.772)	0.014	1.74** (2.32)	0.075
R^2	0.947		0.984	
AdjustedR^2	0.918		0.952	
Durbin-Watson	2.124		1.825	
Residual sum of squares	0.132		0.086	
F statistic	159.219***		11.858***	

Notes: Data in parentheses are t statistics; "***" represents significance at the 1% level; "**" represents significance at the 5% level; "*" represents significance at the 10% level.

Histograms of the residuals indicate that the residuals distribute normally. As there are no abnormal values, the model is effective and achieves highly reliable estimated results. The standard P-P diagram of standardized residuals shows that data points exist regularly around the baseline. Non-parametric tests on standardized residuals show that standardized residuals satisfy normal distribution. Residual errors are eligible for linear regression.

Restoring standardized data $x_1^*,..., x_5^*$, we obtain the equation regressed on the original data $x_1,..., x_6$ and embraced by the principal component in the cluster group:

$$\hat{y} = 10.33\text{-}0.167x_1 + 0.80x_2 - 0.06x_3 - 0.852x_4 + 0.691x_5 - 0.78x_6$$

Similarly, we obtain the equation regressed on the original data $x_1^*,..., x_5^*$ and embraced by the principal component in the non-cluster group.

$$\hat{y} = 10.472 - 0.004x_1 - 0.635x_2 - 1.18x_3 + 1.078x_4 - 0.276x_5 + 0.417x_6$$

Table 12. *Comparison of Variable Coefficients in the Two Sample Groups.*

Samples in	x_1	x_2	x_3	x_4	x_5	x_6
cluster group	-0.167	0.800	-0.060	-0.852	0.691	-0.780
non-cluster group	-0.004	-0.635	-1.180	1.078	-0.276	0.417

Multiple regressive results (see Tables 11 and 12) show that for the cluster group, all factors except state grants (x_2), foreign equity ratio (x_3) and R&D expenditures (x_5) restrain sales. Judging by the magnitude of the coefficients, state grants (x_2), R&D expenditures per capita (x_5), foreign equity ratio (x_3), number of authorized patents (x_1), education index (x_6) and ratio of technical staff (x_4) contribute to sales degressively. This is consistent with previous research, and it indicates that existing clusters in China remain driven by the government. Regarding cluster enterprises, the growth of sales rely heavily on support from government funds and independent research and development. For the non-cluster group, factors in addition to education index (x_6) and ratio of technical staff (x_4) hinder sales. According to coefficient magnitudes, the ratio of technical staff (x_4), education index (x_6), number of authorized patents (x_1), R&D expenditures (x_5), state grants (x_2) and foreign equity ratio (x_3) contribute degressively to sales. Thus, we determine that human capital more effectively enhances the performance of companies beyond clusters.

4.5. Analysis of Empirical Research

Selecting 188 GEM companies listed before 2012 in China, we divide these companies into cluster and non-cluster groups per business area. We employ principal component regression analysis to compare innovation, learning and factor input abilities of the two samples as well as their impact on business performance. After data screening, we have 106 companies in the cluster group and 82 companies in the non-cluster group, indicating small-and medium-sized technology listed companies mostly operate within clusters to make full use of preferential policies and the agglomeration effects of innovation resources. The two sets of samples extracted three main components that embrace the different variables.

The "input factor" reflects the value the company places on R&D investments and on where the R&D capital comes from. Cluster enterprises funding their R&D activities with government grants (x_2) and their own paper (x_5) should comply with the compulsory provision of the cluster management committee whereby membership should devote a certain percentage of the profits to R&D activities, for example, 10 percent. This suggests that innovation is the purpose of the cluster establishment where government supports and corporate R&D investments are equally important. Companies beyond clusters obtain innovation capital primarily from self-owned R&D investments (x_5) and foreign funds (x_3). Variable differences explain that enterprises within clusters can more easily access government policy support. Receiving less support from government, companies beyond clusters focus more attention on foreign innovation drive. Spending on R&D (x_5) highly correlates with the "input factor" in the two sample groups, indicating the GEM listed companies generally attach great importance to R&D activities, irrespective of their geographic location.

The "innovation factor" reflects a company's innovation performance and its sources. For enterprises within clusters, education index (x_6) and the number of authorized patents (x_1) are determinants, and accordingly, they represent the importance of improving staff quality to enhance the learning effects and stimulate creation. For the two sample groups, the number of authorized patents (x_1) is highly correlate with innovation indicators, thus indicating that patents directly reflect corporate innovative performance.

The "learning factor" reflects corporate capacity through internal and external learning to acquire know-how spillovers or transfers. For companies within clusters, the ratio of foreign equity (x_3) and the ratio of technical staff (x_4) are key factors influencing a company's learning ability. For companies beyond clusters, government grants(x_2), education index (x_6) and ratio of technical staff (x_4) are main influencing factors, indicating clusters are more capable of absorbing external know-how, techniques and managerial skills spilled from foreign invested entities. Cluster enterprises are more concerned with internal learning and the enhancement of general quality by attracting advanced talents and skills training, both of which are conductive to creation. For the two sample groups, the ratio of technical staff is highly associated with the learning indicator, indicating the technical personnel are prerequisite for innovation.

Regression results for the cluster and non-cluster groups show that the coefficients of government grants (x_2) are 0.8 and -0.635 and the coefficients of R&D expenditures (x_5) are 0.691 and -0.276, respectively. These results indicate that for enterprises within clusters, state grants and R&D expenditures add one percent, while sales revenues add 0.8 percent and 0.691 percent, respectively. For enterprises beyond clusters, state grants and R&D expenditure add one percent, sales revenues decrease the coefficients by 0.635 percent and 0.276 percent, respectively. This suggests that certain elemental conditions must be satisfied to realize the full effect driven by government support and R&D spending. The collection of innovation elements in clusters is conducive to the positive role of government support and R&D inputs. With respect to the lacking factorial conditions beyond clusters, state grants and R&D investments are conductive to innovation, while lagged or rough processing of industrialization eventually hinders sales growth. For two sample groups, regressive coefficients of the variable education index (x_6) are -0.780 and 0.417 and for technical staff ratio (x_4), the coefficients are -0.852 and 1.078. For companies beyond clusters, staff quality and technical staff ratio improve one percent, sales revenue increases by 0.417 percent and 1.078 percent, respectively, thus suggesting that staff quality and science and technology talents significantly boost performance of businesses beyond clusters. Thus, it is concluded that, technical personnel plays a more important role than staff quality. While these two variables within the cluster group are negatively correlated with corporate performance, this is probably because of the existing lagged process of converting creative achievement into sales, even though the comprehensive quality of employees and technical staff drive innovation. This explains the discriminatory short-term business objective such that high-tech enterprises within clusters give priority to innovation, while companies beyond clusters focus on sales. For the two sample groups, the number of authorized patents (x_1) and ratio of foreign equity (x_3)are notably and negatively associated with sales. For each one additional percentage in the number of patents (x_1), sales revenues decrease by 0.167 percent and 0.004 percent for enterprises within and beyond cluster, respectively. Therefore, innovation performance in cluster enterprises has the greatest effect on sales. Because innovation performance has negative impacts on sales, external funding support from governments or from overseas is crucial. Cluster members are the most incubated entities as they lack marketing channels and market foundations. This, combined with the hysteretic process of turning creative achievements into industrial products, causes creative activities to prominently crowd out sales. For each one additional percentage of foreign equity ratio (x_3), sales revenues in enterprises within and beyond clusters are reduced by 0.06 percent and 1.18 percent, respectively. Because of comprehensive innovative elements and strong absorption capacity, enterprises within clusters can quickly absorb FDI technology spillovers and rapidly respond to the market. Additionally, cluster enterprises are less impacted by crowd-out effects caused by the entrance of foreign investors.

5. Conclusion and Political Recommendation

Based on principal component analysis, this paper constructs three main ingredients of inputs, innovation and learning factors, and then uses multiple regression to compare disparities in the element and their impacts on performance for enterprises inside and outside clusters. The results show the following:

(1) Governments give priorities to existing clusters whose performances are weakly associated with market segmentation, extended value chains, specialization and industrial links. Cluster innovation highly depends on governmental financial support and their own capital investments, thus absorbing less technology spillover from foreign equity. This suggests that in cluster enterprises, endogenous creation dominates and operating performance receives less attention. With respect to the existing stock shortage of capital and technology, Chinese governors should pay more attention to exogenous sources of innovation, encourage foreign equity and venture capital investment, strengthen international cooperation in research and development, and support science and technology development projects of foreign enterprises or R&D institutions.

(2) Talents are the most valuable treasure for high-tech entities. Governments should guide enterprises to improve staff quality by conducting joint trainings or technical exchanges, holding regular staff skills competitions, visiting leading companies and engaging in learning activities with universities and scientific research institutions.

(3) There is a weak connection between cluster innovation and sales performance. Governments should focus on building technical service networks and platforms to industrialize innovative achievements by attracting intermediary service organizations into parks and establishing commercial organizations and clubs to accelerate the process of industrializing creative achievement.

Many other indicators influence innovation performance, some of which are difficult to quantify or are the result of subjectivity. This research adheres to quantifiable and available principles in index selection, but inevitably, it possibly neglects some influencing factors and could thereby report biased results. Most of the GEM listed companies are young, and their financial reports inevitably contain missing data, which affects sample size as well as subsequent analysis. In addition, it is difficult to judge the rationale of the statistical caliber when it is not revealed by enterprises established in various time and location.

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