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EMPIRICAL ARTICLE

Knowledge intensive business services and their impact on innovation in China

Xing Shi · Yanrui Wu · Dingtao Zhao

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Abstract This study investigates the impact of knowledge intensive business services (KIBS) on innovation in China. First, we review the development of KIBS in China by analyzing the agglomeration, utilization, and quality of KIBS. Second, regression techniques are employed to investigate the impact of KIBS on innovation in the Chinese economy. We found that KIBS are becoming a major force in promoting innovation, especially in eastern China. Furthermore, we also found that the effect of KIBS on innovation is highly related to the average level of human capital. Given the findings in this study, we provided some policy suggestions.

Keywords Agglomeration · Innovation · Knowledge intensive business services

1 Introduction

While many studies on technological innovation are focused on the manufacturing industry, the service industry has been virtually ignored for a long time. With the pioneering works of Barras (1986) and Gershuny and Miles (1983), services attracted the attention of researchers in innovation studies during the eighties. But it was in the nineties that researchers' interest in services expanded. Among a variety of service activities, the knowledge intensive business services (KIBS) are of special interest. KIBS, in general, are those services mainly concerned with providing knowledge intensive inputs to the business processes of other organizations, including private and public sector clients'. For example, the advertising, the

X. Shi · D. Zhao
School of Management, University of Science and Technology of China, Hefei, China

X. Shi · Y. Wu (✉)
Economics (M251), Business School, The University of Western Australia, Crawley, WA, Australia
e-mail: yanrui.wu@uwa.edu.au

marketing, the financial services, the consultant services, and the research-related services. They are special due to their close relationship with knowledge and they are often considered as one of the hallmarks of the knowledge-based economy. The roles of KIBS in innovation systems usually involve (a) knowledge exchange; (b) knowledge provision; and (c) knowledge transfer (Miles 2005). Muller and Zenker (2001) pointed out that KIBS act as co-producers and initiators of innovation. Wood (2002) argued that the context-specific relationships between KIBS and their clients cause the spatial agglomeration of KIBS. These studies showed three key dimensions of KIBS, namely, knowledge, innovation, and agglomeration (Muller and Doloreux 2009). In other words, KIBS are highly related to knowledge, can improve innovation greatly and tend to concentrate in metropolitan areas.

To sustain China's rapid economic growth, enhancing the country's innovative capacity has become the key to adjusting the industrial structure and in changing the economic growth pattern of China. Porter (1990) argues that innovative capacity is essential to productivity and that competitiveness can be equated with productivity. Based on this argument, KIBS play an important role in promoting economic competitiveness and growth. In recent years, the KIBS industries have been booming in China, although they are still far behind the same industries in developed countries. Thus, to better understand the contribution of KIBS to innovation and regional disparity in the Chinese context, a number of questions are proposed in this paper. Namely, to what extent do KIBS promote China's innovative capacity? Does the average level of human capital affect the performance of KIBS?

This study first measures the agglomeration, utilization, and quality of KIBS in China, and reviews the growing history and regional development of the KIBS industry. Furthermore, we investigate the impact of KIBS on the output of innovation. Wood (1998) indicated that the growing role of KIBS appears to be an opportunity for developed regions and a threat for peripheral regions. A knowledge-based regional polarization is currently taking place, in which KIBS play a pivotal role (Wood 2005). Therefore, the regional disparity is also considered.

In the section that follows, we provide an overview of the literature with regard to KIBS and their impact. The third section presents the econometric models. After that, Sect. 4 describes the data issues and provides the preliminary analysis of KIBS in China. Empirical analysis and some discussions are presented in the fifth section, while in Sect. 6 we examine the robustness of our findings. Finally, a conclusion and policy suggestions are provided in Sect. 7.

2 Literature review

The definition of KIBS is still being debated (Wood 2002). Miles et al. (1995) define the KIBS industries as: (a) private companies or organizations, (b) based on professional knowledge (related to a specific technical discipline or technical functional domain), and (c) supplying knowledge-based intermediate inputs. Den Hertog (2000) states that "KIBS form a category of service activities which is often highly innovative in its own right, as well as facilitating innovation in other economic sectors, including both industrial and manufacturing sectors." In Bettencourt el al.'s definition (2002), KIBS are considered as "enterprises whose primary value-added activities consist of the accumulation, creation, or dissemination of knowledge for the purpose of developing a customized service or product solution to satisfy the client's needs." Three core elements (Muller and Doloreux 2009) can be derived from these widely accepted definitions, including (a) the term "business services" or specialized services, which are demanded by firms and public organizations and are not produced for private consumption (Strambach 2001); (b) the phrase "knowledge intensive," which can be interpreted in terms of either labor qualification (Miles 2005) or the conditions for transactions between the service providers and the service users or procurers (Hauknes 1999); and (c) the term "knowledge intensive firms," which refers to firms that undertake complex operations of an intellectual nature, in which human capital is the dominant factor (Alvesson 1995). As for the content of KIBS, the nomenclature often follows the National Classification of Economic Activities (NACE), which has become increasingly popular for identifying KIBS in Europe. According to NACE, the KIBS sector primarily includes computers and related activities, research and development (R&D), and other business services.

Considering the significant role of knowledge in KIBS, the definition of knowledge is worth to be specified. Knowledge is a kind of dynamic combination of organized experience, values, related information, and insight, the framework made up by which could constantly evaluate and absorb new experience and information. Knowledge can be divided into two types: the codified knowledge and tacit knowledge (Nonaka and Takeuchi 1995; Polanyi 1967). Codified knowledge is the knowledge can be recorded by media or carried by language, thus it is easy to transfer and manage. However, to understand and explain the codified knowledge needs the tacit knowledge. Tacit knowledge is the informal knowledge that know-how, it is hard to describe or capture by media and language, only can be acquired through informal learning process and is relate to individual's experience, feeling, and opinion. Therefore, compare to the codified knowledge, the tacit knowledge is more difficult to exchange. KIBS, act as a big container, combine various types of highly specialized knowledge, both codified and tacit, in order to develop problem-specific solutions, thus increasing the exchange of otherwise disconnected pools of knowledge and provide professional services (Windrum and Tomlinson 1999).

Furthermore, the function of KIBS is also debated. Some authors adopt what can be described as a management or organizational perspective, and define the role of KIBS as the transfer of knowledge to their clients. Examples include Strambach (2001), Glückler (1999), and Schulz (2000), who emphasized the generation, diffusion, and creation of knowledge through interaction between KIBS and their clients. It is argued that KIBS not only transfer knowledge and information to the users of their services, but that their activities can also be considered as collaborative learning processes (Aslesen and Isaksen 2010). In fact, the resolution of the specific problems facing client firms may lead to the development of new knowledge (den Hertog 2002). Thus, the KIBS play an intermediary role for relevant knowledge, specifically the role of transforming scientific and technical information to tacit knowledge.

Another approach consists of starting with the concept of a national innovation system in relation to the process of innovation (den Hertog 2000; Tether 2005; Camacho and Rodriguez 2008; Naranjo-Valencia et al. 2011). KIBS are assumed to carry out three major functions, acting as the facilitators, carriers, and source of innovation for their client firms (Fischer 2001; Hipp 2000). Specifically, KIBS act as facilitators of innovation when they collaborate with their client firms in the innovation process. They function as the carriers of innovation when they directly participate in innovations by their client firms. Finally, KIBS are sources of innovation when they generate innovations for their client firms.

The above-mentioned literature emphasized the complementarity between customer resources and capacities and the external knowledge provided by KIBS (Muller and Zenker 2001; Tether and Tajar 2008; Cambra-Fierro et al. 2011). By providing expertise, KIBS represent an interface between their customers and the knowledge base available in the entire economy, and hence are a catalyst for innovation (Castellacci 2008; Castaldi 2009). In all cases, the provision of knowledge (tacit and codified) by KIBS is carried out through strong supplier/client interaction (Muller and Zenker 2001; Mas-Verdú 2007). Indeed, the impact of KIBS on innovation will depend on the type and intensity of the relationship between the organization providing the services and the users. For this reason, it seems particularly appropriate to evaluate the impacts of KIBS on the innovation effort in an economy.

Empirical studies focus on different regions. For example, Rodriguez and Camacho (2008) evaluated and compared the R&D diffusion role of a group of KIBS in 11 European countries, with the results showing the existence of a potential “compensatory” role for the imported high-tech services in some countries. Mas-Verdú et al. (2011) considered the drive for innovation in the Spanish economy and the impacts of KIBS using an input–output framework, finding that KIBS are significant net generators of innovation. However, research on KIBS has mainly focused on developed countries, with little attention paid to less developed countries such as China. Although researchers in China are aware of the significant role of KIBS, they primarily focus on the innovation in KIBS themselves, neglecting the impacts KIBS have on innovative capacity and economic growth (Liu 2012). This paper thus fills the void in the literature by exploring empirical evidence of the impact of KIBS on innovation in the context of China as a developing country, introducing the average level of human capital as a method to test the threshold effect.

3 Methods

The goal of this empirical analysis is to explore the impact the agglomeration of KIBS has on innovation at the provincial level. For this purpose, we adopt the framework of the knowledge production function (KPF) introduced by Griliches (1979). In the KPF framework, knowledge creation is modeled as a functional relationship between the inputs and outputs of the knowledge production process (Acs et al. 2002). The concept of KPF has been used to measure the contribution of

R&D and knowledge spillovers to growth in productivity. In the empirical literature, the relationship between R&D input and output is generally represented through a linear or nonlinear polynomial model (Comanor 1965; Vernon and Gusen 1974; Koeller 1995). Symbolically,

$$Y = f(R) + X\lambda + \varepsilon, \tag{1}$$

where Y is the output of innovation, R is the input of innovation, X is a vector of control variables, λ is a vector of unknown parameters, and ε represents the random error term.

Taking the Cobb–Douglas production function as a framework, the basic relationship is

$$Y = AK^{\alpha}L^{\beta}e^{\sum \lambda_k X_k}e^{\varepsilon}, \tag{2}$$

where K and L represent the capital and labor inputs, respectively, A reflects the efficiency of R&D activities, X_k are the factors affecting the efficiency of R&D activities, and α, β, and λ_k are parameters to be estimated. In this study, the output of innovation is measured by the number of patents granted. The capital and labor inputs are defined as the R&D stock and full-time equivalent R&D personnel, respectively.

Furthermore, we augment Eq. (2) by introducing KIBS and the average level of human capital as control variables. To transform Eq. (2) into a linear one which can be estimated using popular econometric packages, we adopt the natural logarithmic form as follows:

$$\ln Y_{it} = \ln A + \alpha \ln K_{it} + \beta \ln L_{it} + \lambda_1 \mathrm{KIBS}_{it} + \lambda_2 \mathrm{HC}_{it} + \lambda_3 \mathrm{KIBS}_{it} \times \mathrm{HC}_{it} + \varepsilon_{it} \tag{3}$$

in which ln A is a constant factor, KIBS refer to the agglomeration of KIBS and HC is the average level of human capital. These variables will be described in Sect. 4. The subscripts i and t represent the region and time and ε_{it} is the stochastic error. The log-linear form of Eq. (3) also implies constant elasticity which makes it for interpretation. It can be estimated using ordinary least squares (OLS). Some econometric issues are involved and will then be discussed in Sect. 5.

4 Data issues and preliminary analysis

The empirical estimation is based on a balanced panel data-set taken from 30 Chinese regions for the period of 2004–2010 (Tibet is excluded due to missing data). The size of the full sample is thus 210. All data employed in this research is drawn from the China Statistical Yearbook (2005–2011) and the China Statistical Yearbook of Science and Technology (2005–2011).

4.1 Measurement of KIBS

Due to variations in world statistic systems, there is no consensus on the division of KIBS categories. To fully use the existing statistical data, this paper, from the view of service production mode, according to the National Industries Classification of

China (GB/T 4754-2011) and the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC Rev. 4. 0), divides the KIBS into four major categories and fourteen sub-categories as shown in Table 1 (Wei et al. 2007).

Two methods are utilized in this study to measure the agglomeration of KIBS. First, following the theory of industrial agglomeration, the location quotient (LQ) index is used to reflect the agglomeration and specialization of KIBS. The equation is expressed as follow:

$$LQ_{ij} = \left(L_{ij} \Big/ \sum_{j=1}^{m} L_{ij} \right) \Big/ \left(\sum_{i=1}^{n} L_{ij} \Big/ \sum_{i=1}^{n} \sum_{j=1}^{m} L_{ij} \right) \tag{4}$$

L_{ij} represents the employment of industry j in region i, m is the number of industries and n is the number of regions. One of the channels through which the KIBS promote the diffusion of knowledge and innovation is through labor mobility. For this reason, the quantity of employment is used in Eq. (4).

To present an alternative way of measuring agglomeration, the density of employment is calculated to measure the spatial density of KIBS

$$\text{Employment density} = (\text{number of employees})/(\text{area of the district}). \tag{5}$$

As KIBS are mainly agglomerated in the urban region, the area of the district refers to the municipal district in each province. Other main variables with descriptive statistics are detailed in Table 2.

In this paper, we present R&D stock using the perpetual inventory method (PIM):

$$R_t = \sum_{i=0}^{t-1} (1-\delta)^i E_{t-i} + (1-\delta)^t R_0, \tag{6}$$

Table 1 The categories of KIBS

KIBS	Sub-categories
Financial services (FS)	Banking
	Security
	Insurance
	Others
Information and communication (IC)	Telecom and information communication
	Computer related
	Software
S&T services (STS)	Research and development
	Professional and technical services
	Engineering and planning management
	S&T exchange and promotion
Business services(BS)	Legal
	Consultancy activities
	Others

S&T science and techonology

where R_t is the R&D stock in period t, E_{t-i} is the R&D expenditure of period $t - i$, R_0 is the initial level of R&D stock, and δ is the rate of obsolescence of the R&D capital.

The initial amount of R&D capital, R_0, is calculated as follows:

$$R_0 = \frac{E_1}{g + \delta}, \tag{7}$$

where g is the growth rate of E, which is estimated using the arithmetic average growth rate in the first 3 years. Following the existing literature, the rate of obsolescence δ is assumed to be 15 % (Griliches 1980). In order to avoid the impact of price fluctuation, we need to find a price index of R&D expenditure. However, in the statistical data available, we are not able to find the specific data collected according to the spending purpose, which also makes it become a difficult problem to establish a price index of R&D expenditure in the field of innovation economics in China. Generally, there are two ways are adopted to deal with this problem. One is to use the GDP deflator to be a substitute (Zhao and Hu 2012). The other one is computed as the weighted average of consumer price index and fixed asset price index (for the R&D expenditure is mainly consist of the consumption of R&D personnel and the expenditure of fixed assets)

$$\mathrm{PI} = 0.55 \times \mathrm{PI_c} + 0.45 \times \mathrm{PI_i}. \tag{8}$$

PI is the R&D deflator we established. $\mathrm{PI_c}$ and $\mathrm{PI_i}$ are the price index of consumer and fixed asset, respectively. The numbers 0.55 and 0.45 are their weights which are widely accepted and used (Kong and Su 2012; Li et al. 2008; Song et al. 2011; Yang and Luo 2011; Zhu and Xu 2003).We use the method proposed by Barro and Lee (2000) to evaluate the average level of human capital. We assume that the years of schooling of illiteracy, primary school (PS), junior high school (JH), senior high school (SH), junior college and above (JCA) are 0, 6, 9, 12, and 16 years, respectively. Thus, the average level of human capital (HC) is calculated as follow:

$$\begin{aligned}\mathrm{HC} = {} & (\text{ratio of PS}) * 6 + (\text{ratio of JH}) * 9 + (\text{ratio of SH}) * 12 \\ & + (\text{ratio of JCA}) * 16,\end{aligned} \tag{9}$$

where the "ratio" refers to the share of population in each group over the total population aged 6 and above.

Table 2 Description of variables

Variable	Description	Mean	Max.	Min.
ln (Y)	ln (number of patents granted)	9.31	11.84	4.25
ln (K)	ln (R&D stock)	14.54	17.19	11.07
ln (L)	ln (R&D personnel full-time equivalent)	10.99	12.75	7.10
ln (KIBS)	ln (LQ index of KIBS)	0.05	2.18	−0.87
	ln (density of KIBS employment)	24.60	157.97	3.12
ln (HC)	ln (average level of human capital)	2.11	2.42	1.85

Source Author's own calculation

4.2 KIBS in China

Since China's reform and opening to international trade, the service industry has experienced rapid growth which has accelerated the upgrading of industry structure, contributing to the transformation of the long-term economic growth pattern in China. This can be seen in Fig. 1, with the ratio of service industry in GDP at about 25 % in 1978, increasing to around 45 % in 2010. This figure has almost doubled in the past three decades. The importance of the service industry can be seen to have grown considerably.

However, in comparison with developed countries, there still remains a huge gap. In Fig. 2, the ratio of service industry employment in developed countries is around 70 %, while China's is just above 30 %. This reflects the fact that the service industry in China is less developed. This is mainly due to the traditional policy of emphasizing material production and ignoring the service sector. It also implies that there is great potential for service sector growth in China. However, another gap, which is even greater, is seen in the structure of the service sector. In Table 3, although both the shares of KIBS value-added in GDP and the service industry are growing modestly, China is still well behind the developed world. In 2006, for example, the share of KIBS value-added in GDP in China was 9.37 %, while comparatively this figure in the United States was 24.87 % (Zhao 2007). In China, the traditional service industries still occupy the dominant position, while the modern service industries are relatively underdeveloped. Thus, it is a tough task to optimize and upgrade the structure of China's service industry by expanding modern services, while still keeping up the pace of growth in traditional services.

The development of KIBS has obviously been uneven across regions in China. It can be seen in Fig. 3 that the KIBS are more agglomerated in the eastern region, and

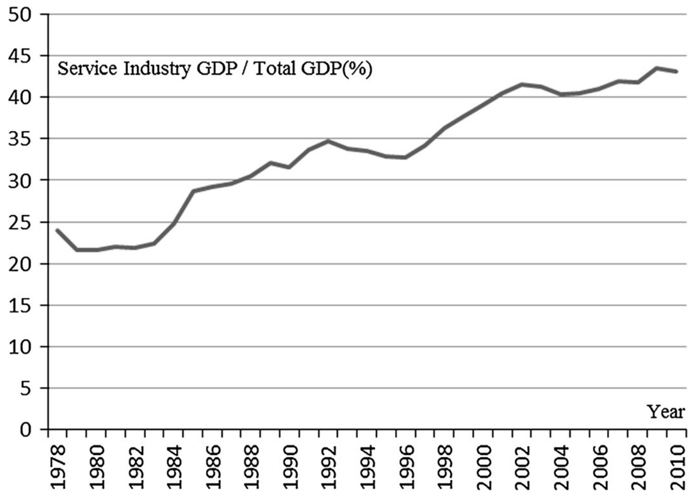

Fig. 1 Service industry GDP shares, 1978–2010. *Source*: China Statistics Yearbook (1979–2011)

that the LQ index of KIBS in central and western regions are very close, though there are some fluctuations in the central region.

At the provincial level, Fig. 4 shows the ten regions with greatest amount of KIBS agglomeration. It has been found that the majority of KIBS are clustered in Beijing (BJ), Shanghai (SH), and Tianjin (TJ), which are all metropolitan cities. Although economic development in Xinjiang (XJ), Shanxi (WSX), and Qinghai (QH) in western China has been relatively backward, the agglomeration of KIBS in these regions is high.

5 Empirical results

The data-set described in the preceding section is applied to the empirical models. The estimation results are shown in Table 4. We first consider the traditional knowledge function with labor and capital inputs only. In Models 2 and 3, the KIBS agglomeration and average level of human capital are introduced separately. Furthermore, the cross-term of the agglomeration and the average level of human capital is considered in Model 4.

In all of the cases, we conducted Hausman tests. The random effect model is then adopted if the Hausman test is not significant. If it is found to be significant, the fixed effect model is more appropriate. In Models 1, 3, and 4, the p values of Hausman test are less than 0.01; this means the hypothesis that the random effect model is preferred is rejected. Hence, the fixed effect models are used. As for Model 2, the p value of the Hausman test is greater than 0.10, thus the hypothesis cannot be rejected and the random effect model is preferable.

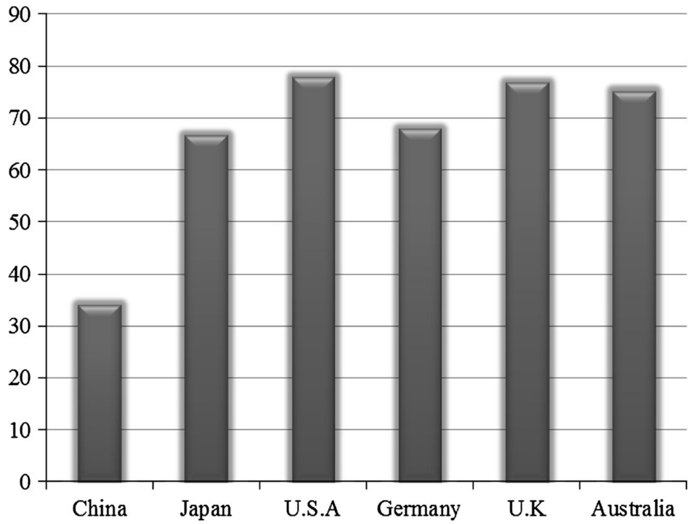

Fig. 2 Service industry employment shares in selected countries, 2008. *Source*: China Statistics Yearbook (2011)

Table 3 KIBS value-added share in GDP and service industry (%)

	2006	2007	2008	2009
KIBS value-added/total GDP (%)	9.37	10.23	10.29	10.81
KIBS value-added/service industry (%)	22.88	24.41	24.61	24.89

Source Author's own calculation

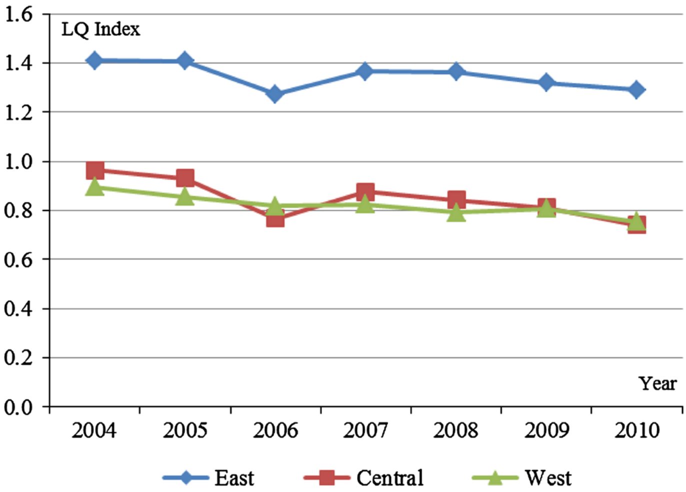

Fig. 3 Trends of LQ index of three regions. *Source*: Authors' own calculation

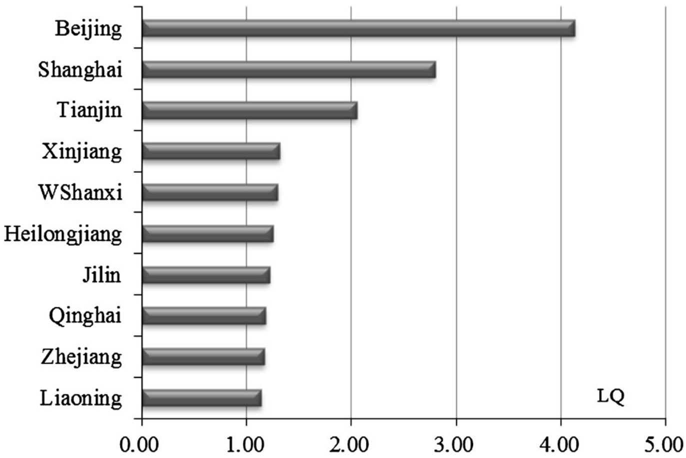

Fig. 4 Ranking of KIBS agglomeration, 2010. *Source*: Authors' own calculation

In all the models, we observe that the elasticity of capital is greater than the labor input. In Model 2, the p value of the KIBS agglomeration is not significant, which means that there is no evidence that KIBS affect the innovation output. However in Model 3, the p value of human capital is 0.000, which is significant at the 1 % level. With the introduction of the cross-term between the LQ and the human capital measurement, ln (LQ) * ln (HC), the results show that the coefficients of KIBS agglomeration and the cross-term are −3.291 and 1.516, respectively. These results are both very significant. Thus, there is a threshold effect of human capital, with a threshold value of 2.171 (3.291/1.516). The average level for China was 2.135 up until 2010.

The impact of KIBS on innovation is positive if ln (HC) is greater than 2.171, while it is negative if ln (HC) is smaller than 2.171. Hence, the impact of KIBS agglomeration on innovation is associated with a high level of human capital. By 2010, only Beijing (BJ), Tianjin (TJ), Shanxi (SX), Liaoning (LN), Jilin (JL), Heilongjiang (HLJ), Shanghai (SH), and Guangdong (GD) had reached this standard. Generally, although the KIBS agglomeration is a significant factor affecting innovation, its impact is limited and is conditional on the level of human capital development.

To further analyze the regional disparity of the impact of KIBS on innovation, we divide China's 30 provinces into three groups; eastern China, central China, and western China. To be specific, eastern China includes Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, and Zhejiang; central China consists of Anhui, Henan, Heilongjiang, Hubei, Hunan, Jilin, Jiangxi, and Shanxi; western China contains Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, Yunnan, and Chongqing. The separate regression results are shown in Table 5. In eastern China, the elasticity of the labor input is smaller than that reported in Table 4, while the elasticity of capital is higher than that in Model 3. The threshold value of human capital is 2.032 and all the provinces in eastern China meet this standard. For central China, the elasticity of labor inputs is much higher than that of the other regions. The threshold value in central China is 2.045, which is higher than the value for the Eastern region.

The labor inputs are not significant in western China, while the elasticity of capital inputs is much lower than in the other regions. The coefficient of the KIBS agglomeration variable, human capital, and their cross-term are all found to be statistically significant. The implied threshold level of human capital in the western region is 2.022. In the western region, Gansu (GS), Guizhou (GZ), and Yunnan (YN) have failed to meet this criterion.

We suppose that these phenomena are mainly due to the uneven development of the regional economy. This was caused by the region's original status and the different supporting policies across regions, which should be considered from the evolutionary perspective (Simmie and Strambach 2006). On a macro-level economic development conforms to a certain path, and since the economy of eastern China is better developed, it follows that the service industries will be better involved. On a micro-level, the better economy status and development environment for both enterprises and talents will definitely attract higher quality firms and human resources, which will create preferable circumstances for KIBS

Table 4 Regression results

Variables	Model 1		Model 2		Model 3		Model 4	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−7.101***	0.000	−7.054***	0.000	−13.020***	0.000	−12.525***	0.000
ln (*L*)	0.267***	0.000	0.309**	0.013	0.289***	0.000	0.305***	0.000
ln (*K*)	0.867***	0.000	0.834***	0.000	0.673***	0.000	0.640***	0.000
ln (LQ)			−0.113	0.310			−3.291***	0.000
ln (HC)					4.038***	0.000	3.921***	0.000
ln (LQ) * ln (HC)							1.516***	0.000
Threshold							2.171	
R^2	0.991		0.822		0.994		0.995	
F statistic	631.013		316.614		973.339		959.949	
Hausman test	Prob. = 0.041		Prob. = 0.113		Prob. = 0.000		Prob. = 0.007	
Effect	Fixed		Random		Fixed		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant p value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

performance. Central China, although under the support of the "Central Rise" policy and owning a good base of science and technology, is confined by their economic base and relative infrastructure conditions. The western region lags behind in many aspects: infrastructure, capital inputs, human capital, technology level, etc. Both the absorption and innovative capacity are low, thus the agglomeration of KIBS will be a huge driving-force both for upgrading industries and elevating innovation.

6 Robustness tests

In order to check the robustness of our results, we consider different measurements of key variables to conduct more regressions. We also set the rate of obsolescence as 20 and 10 % to test the sensitivity.

6.1 Alternative measure of KIBS by employment density

In the previous analysis, the degree of KIBS agglomeration is measured by the LQ index, which represents the comparative advantage and degree of specialization of one industry in one region.

Here we use employment density (ED) to replace the LQ index to test the impact of KIBS on regional innovation from the view of spatial agglomeration. The definition of ED is mentioned in Sect. 4. The results are given in Tables 6 and 7. As per prior research, the Model selection is based on the Hausman test and the details are specified in tables.

Table 5 Regression results of three regions

Variables	Eastern China		Central China		Western China	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−13.733***	0.000	−6.985***	0.000	−13.608***	0.000
ln (L)	0.191**	0.022	0.578***	0.000	0.191	0.381
ln (K)	0.798***	0.000	0.643***	0.000	0.534***	0.001
ln (LQ)	−1.764**	0.026	−9.691***	0.004	−11.579***	0.000
ln (HC)	3.929***	0.000	−0.146	0.903	5.774***	0.000
ln (LQ) * ln (HC)	0.868**	0.014	4.738***	0.002	5.725**	0.000
Threshold	2.032		2.045		2.022	
R^2	0.996		0.914		0.966	
F statistic	1122.427		107.612		117.728	
Hausman test	Prob. = 0.030		Prob. = 0.989		Prob. = 0.067	
Effect	Fixed		Random		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant p value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

Table 6 Robustness test of employment density

Variables	Model 1		Model 2		Model 3		Model 4	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−7.101***	0.000	−7.226***	0.000	−13.020***	0.000	−10.457***	0.000
ln (*L*)	0.267***	0.000	0.204***	0.001	0.289***	0.000	0.285***	0.000
ln (*K*)	0.867***	0.000	0.856***	0.000	0.673***	0.000	0.635***	0.000
ln (ED)			0.344***	0.000			−0.475	0.247
ln (HC)					4.038***	0.000	2.776***	0.000
ln (ED) * ln (HC)							0.341*	0.072
Threshold								
R^2	0.991		0.992		0.994		0.995	
F statistic	631.013		677.036		973.339		960.333	
Hausman test	Prob. = 0.041		Prob. = 0.007		Prob. = 0.000		Prob. = 0.001	
Effect	Fixed		Fixed		Fixed		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant *p* value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

Table 7 Robustness test of employment density in three regions

Variables	Eastern China		Central China		Western China	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−2.631	0.122	−28.050***	0.007	−21.647***	0.000
ln (*L*)	0.203***	0.006	0.444**	0.042	0.049	0.851
ln (*K*)	0.867***	0.000	0.810***	0.000	0.628***	0.000
ln (ED)	−3.665***	0.000	−7.682*	0.052	−5.090**	0.023
ln (HC)	−1.115	0.214	9.111*	0.057	9.626***	0.000
ln (ED) * ln (HC)	1.512***	0.000	3.551*	0.056	2.416**	0.028
Threshold	2.423		2.163		2.106	
R^2	0.996		0.912		0.968	
F statistic	975.384		103.692		124.576	
Hausman test	Prob. = 0.003		Prob. = 0.726		Prob. = 0.061	
Effect	Fixed		Random		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant *p* value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

From Table 6, we found that the results are a little bit different. In Model 2, the coefficient of ED is 0.344 and very significant. But in Model 4, there is no evidence to support the existence of a threshold effect. Like the regression we conducted previously, the regional disparity is also considered here. In the eastern region, the coefficient of the cross-term is 1.512. It also shows a high threshold level of human capital, which is calculated as 2.423. Only Beijing manages to achieve this level.

In both central and western China, the impacts of KIBS on innovation are significant, and there is strong evidence of the existence of a threshold level of human capital at the regional level. The value of the threshold level in central and western China is 2.163 and 2.106, respectively.

6.2 Alternative rates of obsolescence: 20 and 10 %

We set the rate of obsolescence at 20 and 10 %, respectively, to test the sensitivity. In Table 8, it is found that the results are quite similar to those from the previous regression in Table 4, although the elasticity and coefficients are slightly different. We also test the robustness at the 10 % rate. There is no significant difference between the results. Therefore, the detailed results are not shown here.

The regional analysis in Table 9 leads to the same conclusion. The test at the 10 % level is also conducted for this data. It is found that the results are not sensitive to changes in the rate of obsolescence of R&D stock.

To summarize, our regression results consistently show the positive impact of KIBS on regional innovation output. KIBS are becoming a major force in promoting innovation in China. It also can be concluded that the average level of human resources plays a very important role in determining KIBS performance, and that there is strong evidence that the threshold effect of human capital exists in China.

Table 8 Robustness test of 20 % level

Variables	Model 1		Model 2		Model 3		Model 4	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−6.656***	0.000	−6.596***	0.000	−12.637***	0.000	−12.161***	0.000
ln (L)	0.290**	0.016	0.301**	0.013	0.292***	0.000	0.309***	0.000
ln (K)	0.823***	0.000	0.811***	0.000	0.636***	0.000	0.602***	0.000
ln (LQ)			−0.090**	0.417			−3.252***	0.000
ln (HC)					4.111**	0.000	4.004***	0.000
ln (LQ) * ln (HC)							1.499***	0.000
Threshold							2.169	
R^2	0.826		0.826		0.994		0.994	
F statistic	491.459		327.176		919.777		932.007	
Hausman test	Prob. = 0.152		Prob. = 0.266		Prob. = 0.000		Prob. = 0.001	
Effect	Random		Random		Fixed		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant p value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

Table 9 Robustness test of 20 % level in three regions

Variables	Eastern China		Central China		Western China	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	−12.895***	0.000	−6.507***	0.000	−12.862***	0.000
ln (L)	0.229***	0.001	0.589***	0.000	0.115	0.604
ln (K)	0.734***	0.000	0.598***	0.000	0.548***	0.000
ln (LQ)	−0.602	0.528	−10.065***	0.003	−10.921**	0.000
ln (HC)	3.801***	0.000	−0.106	0.931	5.690***	0.000
ln (LQ) * ln (HC)	0.397	0.321	4.918***	0.002	5.395***	0.000
Threshold			2.046		2.024	
R^2	0.996		0.912		0.966	
F statistic	1149.224		104.401		118.156	
Hausman test	Prob. = 0.000		Prob. = 0.979		Prob. = 0.058	
Effect	Fixed		Random		Fixed	

* $p < .1$; ** $p < .05$; *** $p < .01$. A significant p value of Hausman test implies the rejection of the random effect model. All fixed effect models are estimated with cross-section weights, and White cross-section standard errors and covariance

These findings are robust even if we change the measurement of KIBS agglomeration or the rate of obsolescence.

7 Conclusion and policy suggestions

This study applied regional data to examine the impact of KIBS agglomeration on innovation and whether the threshold effect of human capital has existed in China in recent years. It adds to existing literature on KIBS by investigating specifically the impact KIBS have on innovation in a developing region, and by introducing the threshold effect of human capital. It also reviewed the current development and regional distribution of KIBS in China. It is found that KIBS agglomeration affects innovation output positively and significantly, which is consistent with the theory and empirical analysis conducted previously. In comparison with developed countries, KIBS in China are still in the initial stage of development. Furthermore, the performance of KIBS is highly related to the average level of human capital, with the threshold level slightly above the mean for these provinces. Thus, many regions fail to meet this criterion. These results, however, are sensitive to the choice of variables as there may be heterogeneity between variables. Generally, these regressions lead to the same conclusion, although some coefficients change to a certain extent.

Based on these analyzes, we make some policy suggestions. First, the government should increase the support of KIBS development and learn from the successful experiences of developed countries (e.g., United States and the United Kingdom) to increase the role of KIBS in becoming an important source of economic growth. Second, different regions should adopt appropriate policies according to the regional reality. The development of KIBS should meet the demand of other sectors, and both the services supplied by KIBS and the absorptive ability of the services buyer will determine the innovation diffusion (Tseng et al. 2011). Therefore, the awareness of cultivating an open innovation system and a mature network should always be kept in mind. Third, the performance of KIBS is conditional on the level of human capital. The Chinese government should consciously cultivate and introduce specialists in this field as other governments have done (Lin and Lin 2012). Furthermore, KIBS should be considered as being as important as high-tech industries, because otherwise the backwardness of KIBS will restrict the regional innovative capacity.

Finally, there are limitations to this research. We concentrated on the KIBS effects and its combination with human capital, but there are still other elements that affect the regional innovation output. In addition, more in-depth studies could be conducted about the contribution mechanism of KIBS to innovation if data about different kinds of innovation output at the city-level becomes more complete and available in the future.

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