Industrial Agglomeration, University-Industry Collaboration and Patent Output: Evidence From the Chinese High-Tech Industry

BING SUN, RUIHAN ZHANG, AND HONGYING MAO
School of Economics and Management, Harbin Engineering University, Harbin 150001, China
Corresponding author: Bing Sun (heusun@hotmail.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 71774035, and in part by the Natural Science Foundation of Heilongjiang Province under Grant LH2020G005.

ABSTRACT This article analyzes the different effects of industrial aggregation, industry-university collaboration, foreign direct investment and government support on innovation performance and the synergistic effect between them, thereby to identify the determinants of innovation output of Chinese high-tech industry in the period 2009-2018. The results indicate that industrial agglomeration and industry-university collaboration both have a significant positive impact on the patent output of high-tech industries, but the synergistic effect between industrial agglomeration and industry-university collaboration is significantly negative. Meanwhile, both of foreign direct investment and government support could negatively affect the innovation output, while their synergistic effect is positive.

INDEX TERMS Industrial agglomeration, university-industry collaboration, patent output, high-tech industry, open innovation.

I. INTRODUCTION
It is widely recognized that innovation is the main driver for establishing a competitive advantage and generating economic growth [1], [2]. High-tech firms, as carriers of industrial upgrades and transformation, treat the production and use of knowledge as an important factor, making it a critical factor for a country to establish itself on the leading edge of economic and technological advances [3], [4]. A large number of studies have shown that there are obvious phenomena of agglomeration in high-tech industries with competitive advantages, for example, Silicon Valley [5], [6], Cambridge Science Park [7] and the science parks in Singapore [8]. The causes of industrial agglomeration are that geographical concentration can provide firms with easy access to critical resources, lower transport costs, access to customers, and a specialized and skilled labor pool, thereby creating knowledge externality and fostering innovation [9].

With the diffusion of knowledge and innovation, technology spillover speeds up and the shortening of the innovation life cycle, relying solely on R&D on the internal resources of firms is becoming increasingly risky. Thus, the traditional R&D model is increasingly turning into “open innovation” [10]–[12]. Firms can achieve “innovation paradigm transformation” through cooperation with universities and research institutions with technological advantages. Moreover, university-industry collaboration has been widely perceived as a promising tool for enhancing organizational capacity in open innovation—where an organization employs external networks in developing innovation and knowledge [13], as a complementary option to traditional internal R&D [14]. Recently, several nations, including the United States (e.g. [15]), Japan (e.g. [16]), South Korea (e.g. [17]), Singapore (e.g. [18]), and European Union countries (e.g. [19]–[21]), have encouraged firms to cooperate with universities and research institutes to enhance their innovation capability and overall scientific and technological strength.

Since the reform and opening up in 1978, China has become one of the most successful developing countries to attract investment from foreign countries [22]. Corresponding, with the increase of FDI year by year, the innovation output of high-tech industries in China become greater especially in recent years. It affects the innovation activities and
eventually productivity of the local industries and firms in the host country through a wide range of spillover channels which include competition, worker mobility, demonstration effects, and forward and backward linkages [23].

In recent years, the Chinese government’s R&D investment has been increasing, especially with the proposal of the major strategy of building an innovative country. According to the statistical bulletin of national expenditure on science and technology, in 2015, China’s government R&D input was 301.32 billion yuan, an increase of 14.3%, exceeding the growth rate of enterprises’ R&D input. The proportion of government funds was 21.3%, an increase of 1 percentage point over the previous year. The government support for R&D and technological innovation has been increasing. “The 13th Five-Year Plan of National Science and Technology Innovation” clearly stated that we should give full play to the guiding and motivating role of financial science and technology investment, improve the allocation efficiency of financial science and technology investment, and make R&D investment intensity reach 2.5%. Against this background, we need to systematically evaluate the effects of government support policies and explore its effect on innovation output of high-tech industries: are high-tech industry’s innovation output increasing or decreasing when they have received government support?

To our knowledge, on the one hand, whereas previous studies have focused on the characteristics of industrial agglomeration and university-industrial collaboration and the causes of their success, empirical studies of high-tech industries from developing countries in the context of open innovation are rare. Moreover, it is a common phenomenon that industrial agglomeration and university-industry collaboration affect innovation performance simultaneously [24], so it is difficult to fully grasp the real impact mechanism of the innovation performance of high-tech industry from a single side. On the other hand, despite the literature regarding FDI and government support is enough, there is still little consensus regarding their true effectiveness in spurring innovation; indeed, there are few studies on the interaction effects between FDI and government support on innovation output of high-tech industries. To this end, we examine how industrial agglomeration, university-industrial collaboration, FDI and government support influence the innovation output of Chinese high-tech industries from the perspective of innovation knowledge in the context of open innovation, using panel data from Chinese high-tech industries for the period of 2009 to 2018.

The main innovations and highlights of this research are as follows. First, in contrast to most existing studies that mainly focus on developed countries or traditional industries, we clarify the relationships among industrial agglomeration, university-industrial collaboration, FDI, government support and the patent output of high-tech industries from the perspective of innovation knowledge, incorporating some of the unique features of the developing and transitional economy of China. It is important to examine the strategic behavior of high-tech industry in the context of open innovation, which is the most dynamic, technological leader in developing countries [4]. Hence, our study helps to provide new insights into high-tech industry’ patent output and policy implications for the application of “new economic geography” theory based on Western experiences in developing countries.

Second, incorporating industrial agglomeration and university-industry collaboration, FDI and government support into a holistic framework, we systematically explore the influences of industrial agglomeration, university-industry collaboration, FDI and government support on patent output in the context of open innovation and compare the differences between these influences. Specifically, we further analyze the synergistic effects of industrial agglomeration and university-industry collaboration, FDI and government support, respectively, and find valuable results that are different from those in the literature from studies conducting separate analyses of industrial agglomeration and university-industry collaboration (e.g. [23], [25]–[27]). Hence, the findings from our study help to enhance our comprehensive understanding of how the complicated relationship among industrial agglomeration, university-industry collaboration, FDI and government support shapes the patent output of high-tech industries in the context of open innovation at the meso-level.

Finally, based on panel data from Chinese high-tech industries, we treat innovation activities as a dynamic process and advance a measurement model of an influence mechanism of innovation performance in high-tech industries by improving the traditional static model and considering the time effect and endogeneity, thus overcoming the limitations of static research based on cross-sectional study design. This approach also corrects for the deficiencies of the previous research that mainly focused on the relationship between industrial agglomeration or industry-university collaboration or FDI or government support and innovation activities but ignored the time effect and endogeneity. Therefore, thanks to the improvements in the method, our empirical evidence enhances the understanding of the innovation driven development of high-tech industries.

This framework can shed light on three issues: First, how patent output is affected by industrial agglomeration, industry-university collaboration, FDI and government support, respectively, and what the difference is? Second, is there an interactive effect between industrial agglomeration and industry-university collaboration, FDI and government support on patent output? Third, what are the problems and deficiencies of the innovation driven development of China’s high-tech industry? The remainder of the paper is structured as follows. Section 2 provides a literature review of the previous research on the impacts of industrial agglomeration, industry-university collaboration, FDI and government support on innovation. Section 3 describes the empirical model, our data and the estimation techniques. Section 4 explains and discusses the empirical results. Section 5 concludes.
II. LITERATURATURE REVIEW

A. INDUSTRIAL AGGLOMERATION AND INNOVATION PERFORMANCE

Marshall [28] was the first to discover the relationship between industrial agglomeration and innovation. Marshall [28] believed that the concentration of industries in specific areas is conducive to the dissemination and application of new ideas, new knowledge and new skills among enterprises because information flows more smoothly, giving rise to new ideas resulting from a concentration of diverse industries, thus promoting innovation. From the perspective of competitiveness, Porter [30] advanced the definition of industrial cluster and the influential “cluster diamond”. Since then, the subject has been extensively explored, but there is a lack of agreement about the influence of industrial agglomeration on innovation activities.

First, groups of researchers believe that agglomeration has a positive impact on innovation activities. For example, Silvestre and Dalcol [31] used the example of the oil and gas industry in the Campos basin of Brazil and indicated that industrial agglomeration positively affected innovation activities. Then, using 242 four-digit standard industrial classification (SIC) industries in Taiwan, Chang and Oxley [9] concluded that geographic innovation had a significantly positive effect on R&D expenditure and supported the modern theory of industrial clustering regarding innovation spillovers within clusters. Similarly, research by Beule and Beveren [32], Zhang [33] and Xie et al. [34] also suggested that firm agglomeration could promote innovation activities. More recently, a great number of studies have extensively explored the positive relationship between industrial agglomeration and innovation from the perspective of spatial geography. Vásquez-Urrío et al. [20] pointed that being located in a science and technology park increases the likelihood of cooperation for innovation and the intangible benefits of cooperation with the main innovation partner. Using the example of the mobile gaming industry in the Seoul Metropolitan Area, and using spatial analytic methods, Jang et al. [35] confirmed that mobile gaming firms co-locate to form sub-clusters for specializing in specific product innovation activities, and microgeographic location had a key role in boosting different product innovation activities within a city level cluster.

Other groups of researchers hold different views. Beaudy and Breschi [36] concluded that the innovation ability of firms in the traditional Italian industrial clusters is negatively related to the aggregation density of firms in the region by comparing and analyzing the technical innovation output data of 23,872 British firms and 37,724 Italian firms. However, there exists a considerable number of studies reporting that industrial agglomeration has both positive and negative effects on innovation performance. For example, the empirical results of Feldman and Audretsch [37], based on industrial agglomeration and regional innovation in the United States, showed that MAR externalities negatively affected innovation activities, which were positively affected by Jacobs externalities. In contrast, according to Baptista and Swann [38], MAR externalities had a significant positive influence on regional industrial innovation, while the promotion of Jacobs externalities on innovation was not significant. Callois [39] detected two opposite effects of proximity in industrial clusters on process and product innovation by building a microeconomic mode. However, some studies held the view that firm agglomeration should be maintained at a moderate level rather than being too dispersed or too gathered together. Therefore, agglomeration that is both too high and too low would hold back innovation activities (e.g. [40]–[42]).

Summing up the literature review, there is a substantial but controversial body of literature considering industrial agglomeration and innovation activities. More importantly, relatively fewer papers use the example of high-tech industries in developing countries; does “new economic geography” theory, which is based on Western experience, apply to China with reference to the policy-directed agglomeration of high-tech industries in the transitional context of China?

B. UNIVERSITY-INDUSTRY COLLABORATION AND INNOVATION PERFORMANCE

Since Etzkowitz and Leydesdorff [43] proposed a triple helix of university-industry-government relations, which laid a theoretical foundation for the research and development of industry-university collaboration, university-industry collaboration has become an important topic, although its effect on firms’ innovation performance is still a very debated issue.

Some studies agreed that industry-university collaboration has a positive impact on innovation output, including patenting and new products. Regarding patenting, George et al. [44] pointed out that firms have gradually mastered the related knowledge of innovation and patents in cooperation with universities, making more recent business faster and more efficient and increasing the number of patents. They investigated 2457 alliances among 147 biotechnology firms and indicated that university-industrial collaboration had a positive influence on the number of firm patents. Moreover, based on the perspective of the technical association and geographical proximity of the patent, António [25] analyzed the effect mechanism of the university-industrial collaboration and innovation performance and verified the significant positive correlation between them. Analogously, Beule and Beveren [32] also believed that relation and geographical distance between universities and firms both positively affect the achievement of innovative. Additionally, Ponds et al. (2009) modelled the effect of university-industry collaboration networks on knowledge spillovers using an extended knowledge production function framework applied to regions in the Netherlands, and found that the impact of academic research on regional innovation is not only mediated by
geographical proximity but also by networks stemming from university-industry collaboration [45].

Regarding new products, Lööf and Heshmati [46] explored the influence of university-industrial collaboration on firms from the perspective of the sales of new products based on Swedish manufacturing firms. The study suggested that the sales of new firm products increased with the increase in the degree of affinity of the university-industrial collaboration. This finding had also been supported by Belderbos et al. [47], who used large sample data from innovative firms in Holland. More recently, adopting a novel source of data made up of a set of university-industry projects funded by the UK Engineering and Physical Sciences Research Council between 1997 and 2007 and firm-level data available through the UK Office for National Statistics, Scandura [48] detected that university-industrial collaboration had a positive and significant impact on the share of R&D employment. Protogerou et al. [21] concluded that programs facilitating networking with universities may help young companies complement and expand their limited technological resource and knowledge bases, which is conducive to innovative activity. Furthermore, investigating the roles different open innovation partners play in improving economic innovation performance and sustainability innovation performance, Rauter et al. [12] pointed out that increased collaboration with universities, customers, NGOs and intermediaries is beneficial for firms.

Other papers also investigated the effect of various typologies of cooperation but found a mixture of positive and negative effects on innovation performance. For instance, Baba et al. [49] used the estimation of a negative binomial regression model based on a sample of 455 firms’ active in the photocatalysis in Japan to study the effect of university-industry cooperation on innovation. Therein, it was suggested that with “Pasteur scientists” increased firms’ R&D productivity, measured as number of registered patents, in contrast, firms’ collaborations with “Star scientists” exerted little impact on their innovative output. According to Eom and Lee [50], who used the Korea Innovation Survey data, a positive correlation between industry-university and industry-government research institute cooperation and patents generated from new product innovation was found, but there was no correlation in terms of the volume of sales or labor productivity. Using a unique dataset, including firm data sourced from the Capitalia survey covering the period of 1995-2006 and university data gathered from a number of sources, Maitetta [26] found that product innovation was positively related to the geographical proximity to a university but negatively related to the amount of its codified knowledge production. Albahari et al. [24] used data from the Community Innovation Survey for Spain and a survey of science and technology park managers to analyze the relation between universities and innovation outputs. His findings suggested that greater involvement by a university in science and technology parks was positively affected by the number of patent applications but negatively affected by tenants’ innovation sales.

The extant literature has attempted to identify the mechanism influencing university-industrial collaboration and innovation activities, especially innovation performance; but the literature has ignored the interrelationship between university-industrial collaboration and industrial agglomeration, which has an important impact on innovation performance.

C. FDI AND INNOVATION PERFORMANCE

Since the 1960s, the spillover effect of FDI has been widely studied by scholars from various countries. However, the existing research about the impact of FDI on the innovation performance of the recipient country have developed different conclusions.

On the one hand, some scholars agreed that FDI has a positive impact on innovation outputs. Research by Pippopoulou et al. [51] shows that outward foreign direct investment (OFDI) has a positive effect on innovation performance of Chinese emerging-market enterprises’ subsidiaries and that this effect is stronger when the OFDI is directed towards developed rather than emerging countries. Similarly, using provincial data from 1995 to 2000, Cheung and Lin [52] pointed out that there existed positive effects of FDI on the number of domestic patent applications in China.

On the other hand, other studies also investigated the effect of various typologies of FDI but found a mixture of positive and negative effects on innovation performance. For example, Zhang [53] studied China’s provincial research activities with a focus on the spillover-induced productivity and efficiency change. The results showed that spillovers as a result of inflow of foreign investment contribute positively to the performance of overall research activities, however, the productivity effects vary across regions. More recently, Ascani et al. [54] investigated the FDI-innovation relationship in Italian provinces, and suggested that only specific categories of FDI benefit local economies, whilst other types may produce negative outcomes by adopting the Pavitt taxonomy of manufacturing sectors.

Furthermore, theoretical literature on spillover suggests that the impact of FDI on innovation performance is conditional upon various factors. Khachoo et al. [23] proposed that the impact of FDI on innovation and productivity is not uniform but varies across incumbents. Depending on their location vis-a-vis the best practice frontier, incumbents near the frontier receive substantial benefits whereas those residing further down do not realise such benefits. Analogously, Wang and Wu [55] found the significance of geographical proximity and relatively heterogeneous knowledge in FDI spillover effects on domestic innovation by investigating regional FDI knowledge spillover effects on product innovation of China’s indigenous electronic firms. Additionally, research by Feng et al. [22] indicated that the impacts of FDI and environmental regulation on urban innovation have not achieved the desired goal without the other’s cooperation with the use...
of a city-level panel data of 285 Chinese cities from 2003 to 2017.

To sum up, although scholars have made a lot of discussions on FDI and innovation, there are still some inconsistent conclusions, especially for the spillover effect of FDI on emerging countries such as China, whether it is promoting or inhibiting needs to be further clarified and explored.

D. GOVERNMENT SUPPORT AND INNOVATION PERFORMANCE

Since the 1960s, the relationship between government support and technological innovation has been widely studied by scholars. Nelson et al. [56] and Arrow [57] emphasized government support for technological innovation from the perspective of public goods and externalities of technological innovation. Subsequently, the theory of national innovation system represented by Freeman [58] and Nelson [59], and the endogenous technology growth theory proposed by Romer [60] and Grossman and Helpman [61], respectively, emphasize the important position of government in the allocation of innovation resources from the perspective of government functions and the necessity of endogenous R&D investment. According to present literature related to this topic, the specific impact that government support has on innovation performance has yet to be clearly defined as including positive, negative and non-linear effects.

Regarding studies with a positive view, Doh and Kim [62] used the technological development assistance funds as a proxy for governmental support policies for SMEs in the regional industries in Korea, and pointed out that a positive relationship exists among the technological development assistance by the Korean government and patent acquisitions and new design registrations of regional SMEs. Analogously, based on the data from small and medium-sized enterprises (SMEs) in biotechnology in South Korea between 2005 and 2007, Kang and Park [63] found that government support through project funding had far-reaching direct and indirect influences on firms’ innovation output by stimulating internal R&D activities and domestic upstream and downstream collaborations.

Yet concerning the negative view of government support, Catozzella and Vivarelli [64] thought that innovative productivity is negatively affected by the subsidy; as a result of government intervention, supported firms appear to exhaust their advantage through merely increasing their innovative expenditures by using a sample of Italian firm-level data (CIS3); However, some studies suggested that the effect of government support has effective thresholds and intervals. For instance, Lin and Luan [65] used the sample data of listed wind power enterprises from 2012 to 2018 to evaluate the innovation efficiency of Chinese wind power industry. Their results showed that in the short term, government subsidies inhibit the improvement of innovation efficiency of Chinese listed wind power enterprises, but it is not significant. In the long term, there exists a U-shaped relationship between government subsidies and innovation efficiency.

Apparently, most of these studies have tried to identify the effect of government support on innovation performance, however, few focuses on the synergistic influence of FDI and government support on innovation output, especially in China, which is an emerging country, a major recipient of FDI and implemented the policy of innovation-driven development.

III. METHODOLOGY

A. MODELS

Innovation is the construction of the knowledge production function, and new production factors and production conditions are reconfigured into a production system [66]. Considering the impact of R&D and knowledge spillover on innovation performance, Jaffe [67] proposed the knowledge production function, and its basic hypothesis is:

\[ Y = f(R&D) \]  (1)

Subsequently, Jaffe [67] believed that production inputs included R&D investment and labor and capital, and the following improvements were made to the knowledge production function.

\[ Y = f(K, L) \]  (2)

Based on the improved Griliches-Jaffe knowledge production function, this study further expands this function model by taking into account industrial agglomeration, university-industrial collaboration, foreign direct investment and government support in the innovative output function and establishes a knowledge production function following Cobb Douglas as follows.

\[ PAT_{it} = A \leftrightarrow AGLO_{it}^{a_1} \leftrightarrow UIC_{it}^{a_2} \leftrightarrow FDI_{it}^{a_3} \leftrightarrow GOV_{it}^{a_4} \leftrightarrow RDL_{it}^{a_5} \leftrightarrow SIZE_{it}^{a_6} \leftrightarrow COM_{it}^{a_7} \leftrightarrow \varepsilon_{it} \]  (3)

Therein, \( i \) refers to the area, \( t \) represents the year, \( A \) is the constant, \( a_1(i = 1,...,6) \) is the elastic coefficient, and \( \varepsilon \) represents the stochastic error term. \( PAT \) refers to the patents from a high-tech industry, \( AGGLO \) refers to the industrial agglomeration of a high-tech industry, \( UIC \) stands for the university-industrial collaboration of a high-tech industry, \( FDI \) is foreign direct investment (FDI), \( GOV \) refers to the government support, \( RDL \) represents the R&D investment of a high-tech industry, \( SIZE \) represents the regional population size, and \( COM \) is market competition.

Based on Model (1), Model (2) and Model (3), we provide further detailed analysis as follows.

Aiming at industrial agglomeration, university-industrial collaboration, foreign direct investment, government support and control variables, the knowledge production function becomes:

\[ \text{In } PAT_{it} = A + \beta_1 \text{In } AGGLO_{it} + \beta_2 \text{In } UIC_{it} + \beta_3 \text{In } FDI_{it} + \beta_4 \text{In } GOV_{it} + \beta_5 \text{In } RDL_{it} + \beta_6 \text{In } SIZE_{it} + \beta_7 \text{In } COM_{it} + \mu_i + \varepsilon_{it} \]  (4)
Then, considering the effect of time delay, the knowledge production function becomes:

\[
\text{In } PAT_{it} = A + \beta_1 \text{In AGGLO}_{it-1} + \beta_2 \text{In UIC}_{it-1} + \beta_3 \text{In FDI}_{it} + \beta_4 \text{In GOV}_{it} + \beta_5 \text{In RDL}_{it} + \beta_6 \text{In SIZE}_{it} + \beta_7 \text{In COM}_{it} + \mu_i + \epsilon_{it}
\]

This research comprehensively compares and analyzes these models, which take into account industrial agglomeration, university-industry collaboration, foreign direct investment, government support, and use a multiple hysteresis model. Furthermore, considering the synergy effect between industrial agglomeration and university-industry collaboration, the synergy effect between foreign direct investment and government support on the patent output of high-tech industries, we use the product of industrial agglomeration and government support to capture the interaction effects above, respectively. Thus, an econometric estimation of the knowledge production function would involve the synergy effect as follows.

\[
\text{In } PAT_{it} = A + \beta_1 \text{In AGGLO}_{it-1} + \beta_2 \text{In UIC}_{it-1} + \beta_3 \text{In FDI}_{it} + \beta_4 \text{In GOV}_{it} + \beta_5 \text{In RDL}_{it} + \beta_6 \text{In SIZE}_{it} + \beta_7 \text{In COM}_{it} + \beta_8 \text{In AGGLO}_{it-1} + \mu_i + \epsilon_{it}
\]

B. OPERATIONALIZATION OF VARIABLES

1) DEPENDENT VARIABLE

Our dependent variable aims at measuring the innovation performance of high-tech industries from the perspective of knowledge. Patents, as the most valuable output of innovation activities, are a proper indicator of industrial and regional innovation performance [44], [68], [69]. On the one hand, the previous literatures indicated that the patent applications bound by the censorship of the patent authority to a lesser extent could reflect the true level of technological innovation. On the other hand, the uncertainty of patent applications is small and there is no time lag for patent licensing; thus, patent applications are stable, easy to obtain and timely [24], [70], [71]. Therefore, we use patent applications (PAT) by high-tech industries as the dependent variable.

2) INDEPENDENT VARIABLES

First, we identify industrial agglomeration (AGGLO) as the independent variable for patent output because agglomeration is an important location feature of the development of high technology industries, which plays a key role in promoting innovation activities [72]. We measure the industrial agglomeration of high-tech industries by the location entropy index, and the formula is calculated as follows.

\[
\text{AGGLO}_{ij} = \frac{\sum_{i} E_{ij}}{\sum_{j} \sum_{i} E_{ij}}, \text{ wherein, i stands for the region, and j represents the industry. The location entropy index is regarded as the relative level of the degree of agglomeration of an industry in a region, which can be calculated by output or employment data. Using high-tech industries as an example, we adopt output data in the calculation because the employment data may be affected by the serious problem of surplus labor in state-owned enterprises, and the difference in the seriousness of the problem of surplus labor in different regions and different industries will lead to the deviation of the location entropy index calculated by the employment data.}

Second, we identify university-industrial collaboration (UIC) as one of independent variables for patent output because university-industrial collaboration in the context of open innovation is an important channel for firms to obtain external innovation resources [13], [14] and an important factor of innovation performance [73], [48]. Based on regional technology gap theory, Cai et al. pointed out that the differences in R&D expenditure distribution in various regions can roughly reflect the technology gap among regions.

As an important part of the regional R&D funds, the difference in space distribution not only represents the active degree of cooperation among provinces and cities but also reflects the gap in the regional technical level to a large extent. Specifically, we measure university-industrial collaboration by the sum of “firm funds within the scientific and technological funds of higher universities” and “firm funds within scientific and technological funds raised by research and development institutions” of all the provinces and cities in the China Science and Technology Statistics Yearbook.

Third, foreign direct investment (FDI) is an important channel for a host country to obtain international knowledge spillovers and create innovative ability, which has a positive effect on promoting technological progress and innovation performance through the technology spillover effect [55]. Thus, FDI is also included as an explanatory variable. In our study, foreign direct investment is measured by the actual utilization of FDI data in various provinces and municipalities.

Forth, the government plays an important role in guiding and coordinating enterprise innovation activities through financial support [57]. This article uses the proportion of government funds in R&D funds of high-tech industries to represent government support (GOV).

3) CONTROL VARIABLES

First, R&D investment (RDL), as the traditional and innovation resource factor, is an indicator that could not be ignored in affecting innovation output, mainly including labor and capital in the R&D sector [67]. Therein, R&D labor is generally measured by the number of staff employed in the R&D sector and R&D capital measured by R&D expenditure [71]. Considering the high correlation between the number of staff employed in the R&D sector and R&D expenditure, we only use the number of staff employed in the R&D sector to measure R&D investment.
Then, the social population is open and inclusive, and the population with steady growth is a key factor for regional success in achieving innovation and maintaining innovative advantages. Thus, we use the size of the total population in a region to indicate the agglomeration size (SIZE).

Finally, previous studies have suggested that market competition is the driving force of innovation output and plays a key role in patent applications and patent tendency [74]. Following Blazsek and Escribano [74]'s approach, we use the number of high-tech firms to reflect the intensity of market competition (COM).

4) DATA SOURCE
The dataset in this study was sourced by the CHINA STATISTICAL YEARBOOK ON HIGH TECHNOLOGY INDUSTRY, the CHINA STATISTICAL YEARBOOK ON SCIENCE AND TECHNOLOGY, the CHINA STATISTICAL YEARBOOK and CHINA POPULATION & EMPLOYMENT STATISTICS covering the 2009-2018 period.

α: REGARDING THE AIMS AND SCOPE OF DATABASE
① The CHINA STATISTICAL YEARBOOK ON HIGH TECHNOLOGY INDUSTRY is compiled by the Department of social science, technology and cultural industry statistics according to the classification of high-tech industries (manufacturing industries) issued by the National Bureau of statistics. The aim of the database is to reflect the development status and international competitiveness of China’s high-tech industry, and meet the needs of national macro-control departments in formulating and adjusting industrial policies and industrial development plans.

This database collects the annual production and operation, R&D and related activities of China’s high-tech industry as well as the relevant international comparative data. It comprehensively describes the basic situation of China’s high-tech industry development. It is the main reference database for the relevant management departments and all sectors of society to understand the development of China’s high-tech industry. The database is divided into four parts. The first part mainly reflects the production and operation of high-tech enterprises, the second part mainly describes the R&D activities, new product development and sales, patents, technology acquisition and transformation, and R&D institutions of high-tech enterprises. The third part is the international comparison data, which is arranged according to the statistics of high-tech industries published by the world bank and other international organizations. The fourth part is the appendix, including the classification of high-tech industry (manufacturing industry), the explanations of contrast revision and the explanations of main statistical indicators.

② The CHINA STATISTICAL YEARBOOK ON SCIENCE AND TECHNOLOGY is provided by the Department of social science, technology and cultural industry statistics, China’s National Bureau of Statistics, reflecting the annual situation of science and technology activities in China, which includes the science and technology statistical data of 31 provinces, autonomous regions, municipalities directly under the central government and relevant departments of the State Council. The YEARBOOK is divided into ten parts. Specifically, the first part is the comprehensive statistical data reflecting the scientific and technological activities of the whole society; The second part, the third part and the fourth part are the statistics of science and technology activities of industrial enterprises, research and development institutions, and universities, respectively; The statistical data of high-tech industry development is presented in the fifth part; The sixth part collected the statistical data of enterprise innovation activities. The seventh part is the statistical data of national science and technology plan. The eighth part is the statistical data of scientific and technological achievements. The ninth part reflects the information about the activities of the comprehensive technical service department and the Association for science and technology; The last part collected international science and technology statistics.

③ The CHINA STATISTICAL YEARBOOK is compiled by the China’s National Bureau of Statistics, containing the annual economic and social statistics of the whole country and of provinces, autonomous regions and municipalities directly under the Central Government, as well as major national statistics of several important historical years and recent years. It is an informative annual publication that comprehensively reflects the economic and social development of the People’s Republic of China.

④ The CHINA POPULATION & EMPLOYMENT STATISTICS is provided by the Department of population and employment statistics, China’s National Bureau of Statistics, focusing on comprehensively reflecting China’s population and employment situation. It collects the main data of population employment statistics of the whole country, provinces, autonomous regions and municipalities directly under the central government, and appendix the relevant data of some countries and regions in the world.

The selection process and reasons of variable data sources, areas and the time span of this article is as follows:

Firstly, we use the CHINA STATISTICAL YEARBOOK ON HIGH TECHNOLOGY INDUSTRY to obtain the data source of patent applications (PAT), industrial agglomeration of high-tech industries (AGGLO), (GOV), (RD), and (COM). Secondly, we adopt the CHINA STATISTICAL YEARBOOK ON SCIENCE AND TECHNOLOGY to receive the data of (UIC). Then, this article uses the CHINA STATISTICAL YEARBOOK to acquire the data of (FDI). Finally, this article adopts the CHINA POPULATION & EMPLOYMENT STATISTICS to gain the data of (SIZE).

Then, there are 34 provincial-level administrative regions within the territory of China, including 23 provinces, 5 autonomous regions, 4 municipalities and 2 special administrative regions. Because of the lack of statistical data in Tibet, Qinghai, Xinjiang, Inner Mongolia, Hongkong, Macao and Taiwan, which are not conducive to the analysis of the panel data, we excluded these regions, thus, the observations
TABLE 1. Descriptive statistics of our samples.

| variable | mean  | p50   | variance | min   | max   | N    |
|----------|-------|-------|----------|-------|-------|------|
| y        | 7.44  | 7.60  | 2.50     | 2.89  | 11.57 | 270.00 |
| AGGLO    | 0.74  | 0.57  | 0.38     | 0.07  | 2.80  | 270.00 |
| UIC      | 11.03 | 11.24 | 2.17     | 5.80  | 13.82 | 270.00 |
| FDI      | 1558.77 | 624.00 | 5.8e+06  | 25.00 | 19235.00 | 270.00 |
| GOV      | 0.11  | 0.08  | 0.01     | 0.01  | 0.42  | 270.00 |
| RDL      | 23643.32 | 10306.00 | 1.8e+09  | 392.00 | 2.9e+05 | 270.00 |
| SIZE     | 8.29  | 8.38  | 0.46     | 6.44  | 9.34  | 270.00 |
| COM      | 1040.49 | 633.00 | 2.0e+06  | 14.00 | 8525.00 | 270.00 |

of this article are the 27 provincial administrative regions within the territory of China, excluding Tibet, Qinghai, Xinjiang, Inner Mongolia, Hongkong, Macao and Taiwan.

Finally, it should be noted that the reasons of selecting for the period of 2009 to 2018 are as follows: on the one hand, because the National Bureau of Statistics of China carried out the reform of income and expenditure items in 2007, there has been no statistical data of enterprise loss subsidy and policy subsidy in China Statistical Yearbook since 2008. As the first year of the reform, some provinces lacked data and inconsistent statistical formulations, the data were not robust enough. Thus, to ensure adequate comparability and accounting and auditing standards, we set 2009 as the starting year. On the other hand, because the data for the high-tech industry in 2019 are not yet available, in other words, 2018 is the most recent data available so far. Therefore, our sample period is from 2009 to 2018.

From what has been discussed above, the sample of this study includes 27 provincial administrative regions in China in the period of 2009 to 2018. Table 1 reports the descriptive statistics of our samples.

C. ECONOMETRIC TECHNIQUE

First, we used the F test to determine which is better a mixed OLS model or a fixed effect model, and B-P test was used to confirm the choice of a mixed OLS model or a random effect model. The F test and B-P test statistics are statistically significant in our models, indicating that both fixed and random effects are better than a mixed OLS. On this basis, the Hausman test was adopted to determine the fixed effect and random effect. The Hausman test is also significant, suggesting that fixed effect is more suitable to estimate than random effect in this study. Furthermore, the tests for heteroscedasticity, serial correlation and cross-section correlation were estimated. We found there was heteroscedasticity, serial correlation and cross-section correlation, thus, we used a Driscoll-Kraay standard error adjustment to estimate again. Finally, the robustness of the estimated results was tested, and the explanatory variables were remeasured to verify the robustness of the research conclusions.

IV. EMPIRICAL RESULTS AND DISCUSSIONS

A. INDUSTRIAL AGGLOMERATION, UNIVERSITY-INDUSTRY COLLABORATION, FDI, GOVERNMENT SUPPORT AND PATENT OUTPUT OF HIGH-TECH INDUSTRIES

The results from estimating the panel system equations are summarized in Table 2. As shown in Table 2, whether or not the time delay is considered, the results of the F test, B-P test and Hausman test all support the selection of the fixed effect, so we obtain the estimation results of the fixed effect, which are model FE (4) and model FE (5). Specifically, Model FE(4) is estimated by including all the explanatory variables and control variables, whereas Model FE(5) includes the effect of a time delay. Further, we find there is heteroscedasticity, serial correlation and cross-section correlation; thus, we use a Driscoll-Kraay standard error adjustment to estimate again and obtain model FE_DK(4) and FE_DK(5).

First, regarding the effect of industrial agglomeration on patent output, in Model FE(4) and Model FE_DK(4), the coefficient for AGGLO is positive but not statistically significant. However, the coefficients for AGGLO (lag one) in Model FE(5) and Model FE_DK(5) are positively associated with patent output and significant at the 1% statistical level. These results suggest that AGGLO has a positive and hysteretic influence on the innovation output of the Chinese high-tech industry.

As discussed in the agglomeration literature, there are several reasons for patent output increases. First, firms belonging to spatially concentrated industries may enjoy the advantages brought about by positive agglomeration externalities, such as the promotion of the specialization of inputs of production factors and labor pool, as well as technological and knowledge spillovers, and so on [77]. Second, geographical proximity reduces uncertainty; it reduces search costs [37] and increases the likelihood of an explicit search for innovation partners [78]. Additionally, geographical proximity contributes to the building of trust, which reduces the transaction costs involved in joint projects and results in more stable and longer lasting relationships [79].

Our results support the theoretical predictions regarding the agglomeration-innovation nexus, validating the
B. Sun et al.: Industrial Agglomeration, University-Industry Collaboration and Patent Output

TABLE 2. Influences of industrial agglomeration, university-industrial collaboration, FDI and government support on patent output.

|         | FE(4)  | FE(5)  | FE_D  | FE_D  |
|---------|--------|--------|-------|-------|
| AGGL    | 0.0812 | 0.0812 | 0.0812 | 0.0812 |
| O       | 0.39   | 0.50   |       |       |
| UIC     | 0.357* | 0.357* | 0.357* | 0.357* |
| FDI     | -      | -      | -     | -     |
| GOV     | 2.200*** 1.912** |       |       |
| RDL     | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| SIZE    | 10.36* 8.158 10.36* 8.158* |       |
| COM     | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| L_AG    | 0.342 0.342* |       |
| GLO     | (1.72) | (4.45) |       |       |
| L_UIC   | 0.568 0.568* |       |
| Const   | -      | -      | -     | -     |

TABLE 2. (Continued.) Influences of industrial agglomeration, university-industrial collaboration, FDI and government support on patent output.

|         | Intra | 3.897* | 3.321 | -- | -- |
|---------|-------|--------|-------|----|----|
| group   | *     | **     |       |    |    |
| autocorrelation test |    |        |       |    |    |
| Inter   | 77.693 | 51.03 | -- | -- | -- |
| group   | ***   | 6***   |       |    |    |
| contemporaneous correlation |    |        |       |    |    |
| t statistics in parentheses | * p<0.05, significant at the 5% level |
|                                   | ** p<0.01, significant at the 1% level |
|                                   | *** p<0.001, significant at the 0.1% level |

application of agglomeration in promoting innovation activities. It is also consistent with those findings using firm-level panel datasets in developed countries, e.g., Belgium (e.g. [32]) and South Korea (e.g. [35]). More importantly, our results are contrary to those of the studies that believe that firm agglomeration should be maintained at a moderate level rather than allowing it to become too dispersed or too gathered together so that both too high and too low agglomeration would inhibit innovation activities [40]–[42]. This is mainly because our research background and the research object are different.

Second, concerning the influences of UIC, overall, the estimated results are basically the same in these models. Considering the fact that the multivariate lag model based on the Driscoll-Kraay standard error adjustment, FE_DK (5), has the best degree of fit and more practical economic meaning, we focus on the estimated result in the model FE_DK(5). It is obvious that the coefficient for UIC (lag one) is positive and statistically significant (p<0.001), implying that university-industry collaboration has a positive influence on patent output. It should be noted that, both of the coefficient values for UIC in Mode FE(5) and Model FE_DK(5) are 0.568, higher than those in Model FE(4) and Model FE_DK(4), being 0.357. These results indicate that the effects of UIC are lagging.

Because universities and scientific research institutions do not directly contact the market in China, there is a hysteretic nature and deviations between the innovative achievements and market demands, thereby leading to the lag and low demand matching in the process of shifting innovative achievements to social productivity.

These findings are consistent with those in the studies (e.g. [44], [48]) focusing on developed countries, which indicate that the current period university-industrial collaboration has a positive effect on the number of firm patents, and moved to a step further to adding the time lag. Thus, the conclusion of the lag effect supports the view of Ponds et al. [45] who
pointed out that university R&D (lagged) has a positive and significant relationship with innovation, suggesting the presence and lagging of academic knowledge spillovers within the regions having a university, even if our models are not exactly the same as theirs.

Third, turning to the effect of FDI, overall, the estimated results are basically the same in these models. Looking at the estimated result in the model FE_DK(5) presented in Table 2, the coefficient for FDI is negative and statistically significant ($p < 0.001$), suggesting that FDI hinder the development of regional patent output to some extent.

Concerning the reasons of the negative results of FDI on regional patent output, a more likely explanation is perhaps a measurement issue, whereby at the firm-level it is positive [51], but at the regional level it is not, perhaps because other kinds of R&D expenditure are lagging, thus suggesting some kind of lack of regional absorptive capacity. Additionally, it is also possible that foreign direct investment is mainly concentrated in the host country’s relatively weak capital and technology-intensive industries, with obvious competitive advantages, thus crowding out the domestic industries of the host country, resulting in a serious decline in the market share of domestic enterprises.

Our results are contrary to the empirical evidence of Piperopoulos et al. [51], which showed that OFDI has a positive effect on innovation performance of Chinese EMEs’ subsidiaries. The reason for this difference may be that, as described in the review article by Perkmann et al. [80], the validity and comparability of results are hampered by the way measures are constructed, and the use of different measures also impedes comparisons across studies, which are also indicated in the study of O’huallachain and Leslie [27].

Forth, as for the government support and regional patent output, all the estimated results in Model FE(4), Model FE_DK(4), Mode FE(5) and Model FE_DK(5) are negative and significant shown in Table 2. In other words, the higher the government support are, the lower the patent output would be. The reason may be that the higher the government subsidies is, the more it squeezes out regions and enterprises’ investment in research and development. However, regions and enterprises do not develop a good utilization plan and management mechanism for the government support, which results in the ineffective allocation of innovation resources and the decline of innovation output.

These results are in line with the finding of O’huallachain and Leslie [27] which suggests that increased government R&D expenditure has a negative influence on patent output in the United States. Additionally, we have moved to a step further to delineating the negative impact of the government support on patent output in a different and emerging country context, China.

**B. THE SYNERGISTIC EFFECTS BETWEEN AGGLO AND UIC, FDI AND GOV**

To identify the relationships between AGGLO and UIC, FDI and GOV in shaping the patent output of high-tech industries, we join the interaction terms of AGGLO and UIC, FDI and GOV, thereby obtaining Model FE(6) and FE-DK(6) presented in Table 3. Interestingly and surprisingly, the interaction term in Model FE(6), AGGLO$^*$ UIC, is negative and significant ($p < 0.001$), which is in line with the result of Model FE-DK(6), supporting the above basic model selection and estimation results. Apparently, our results suggest that the synergistic effect of AGGLO and UIC on patent output is negative.
TABLE 4. Robustness check.

|                | FE-DK        | FE-DK        | FE-DK        |
|----------------|--------------|--------------|--------------|
|                | (4)          | (5)          | (6)          |
| AGGL O         | 0.0738       |              |              |
|                | (0.43)       |              |              |
| UIC            | 0.337*       | -            |              |
|                | (3.30)       |              |              |
| FDI            | -            | -            |              |
|                | 0.000152**   | 0.000115**   | 0.000187**   |
|                | *            | *            | *            |
|                | (-13.82)     | (-7.51)      | (-8.95)      |
| GOV            | -2.387*      | -2.043*      | -            |
|                | 2.213***     |              |              |
|                | (-3.00)      | (-2.99)      | (-5.24)      |
| R&D            | 0.000617     | 0.000613     | 0.000624     |
|                | 2***         | 4***         | 2***         |
|                | (11.07)      | (8.77)       | (7.56)       |
| SIZE           | 11.82***     | 9.337***     | 7.649***     |
|                | (8.42)       | (6.35)       | (5.37)       |
| COM            | 0.000427     | 0.000312     | 0.000646     |
|                | *            | *            | *            |
|                | (6.21)       | (2.41)       | (3.79)       |
| L_AG           | 0.375**      | 7.245*       |              |
|                | (4.63)       | (3.11)       |              |
| L_UIC          | 0.578***     | 0.765***     |              |
|                | (7.34)       | (7.73)       |              |
| GLO            |              |              |              |
| L_AG × GLO     | -0.608*      |              |              |
|                | (-2.95)      |              |              |
| FDI × GLO      |              |              |              |
|                | 0.00131*     |              |              |
| GOV            |              |              |              |
| Const          | -            | -            | -            |
| R-squared      |              |              |              |
| t statistics in parentheses |
* p<0.05, significant at the 5% level
** p<0.01, significant at the 1% level
*** p<0.001, significant at the 0.1% level

The reasons for this phenomenon may be complex. Specifically, first, a more likely explanation for the negative result is perhaps a measurement issue, as suggested in the research of Charlot et al. [76]. “Concerning regional-level studies based on the knowledge production function, there is a large and rapidly increasing amount of empirical literature whose results are difficult to summarize”. Some of these studies have produced comparable results (e.g., Oh Uallachain and Leslie, 2007; Ponds et al., 2010). However, the comparison with such studies is not straightforward because they use different econometric specifications, such as cross-sections [27], pooled panel data [45], or one-way fixed effects models; Second, perhaps because other kinds of R&D expenditure are lagging, thus suggesting some kind of lack of regional absorptive capacity; The final cause maybe that universities use diverse channels to transfer knowledge, including collaborative research, contract research, consulting and other forms of knowledge exchange [80], and these transfers are not always local [45].

It should be noted that the context-specific nature of most published research makes it difficult to form generalized conclusions. It seems plausible that countries with different higher education and public science systems, different stages of economical development and different innovation systems will exhibit different patterns of university-industry relations, and different antecedents and consequences [80].

Considering the synergistic effect of FDI and GOV, the interaction term in Model FE(6) in Table 3, FDI × GOV, is positive and significant (p<0.001) with the value of 0.00121, which is in line with the result of Model FE-DK(6), indicating that the synergistic effect of FDI and GOV could promote the development of patent output. The reason is that government support can better stimulate the technology transfer of transnational corporations, promote the upgrading of domestic high-tech industries, and improve the innovation and competitiveness of products.

C. ROBUSTNESS CHECK

To obtain robust estimates of the influences of AGGLO, UIC, FDI and GOV on patent output, we replace the patent applications (PAT) with the number of patent applications for invention (INV) to re-estimate all the models. Estimates using the Driscoll-Kraay standard error adjustment approach are displayed in Table 4. Compared with the results in Table 2 and Table 3, Table 4 shows that the estimation results are quite similar. Specifically, industrial agglomeration and university-industrial collaboration both have a significant positive impact on the patent output of high-tech industries, but the synergistic effect between industrial agglomeration and university-industrial collaboration is negative, which is consistent with the above findings. Meanwhile, FDI and government support both have a significant negative influence on the patent output of high-tech industries, while their synergistic effect is positive, which is in line with the above results. Therefore, the regression results in our study are robust.

V. CONCLUSION

Using panel data from Chinese high-tech industries for the period of 2009 to 2018, we examine the complex impacts of industry agglomeration, university-industrial collaboration, foreign direct investment and government support on patent output in the context of open innovation, thus, some conclusions have been summarized.
First, industrial agglomeration can significantly increase the patent output of high-tech industries; in other words, the industrial agglomeration increases by 1%, and the patent output will increase by approximately 0.342%, suggesting that industrial agglomeration, as a spatial organization form, is an important channel to enhance innovation performance.

Second, university-industry collaboration positively influences the patent output of high-tech industries, indicating that university-industry collaboration could be seen as an important factor influencing regional innovation output due to the knowledge spillovers.

Third, compared to industrial agglomeration, the spillover effect of university-industry collaboration on innovation output is more significant, indicating that the increase of innovation output promoted by university-industry collaboration is more than that of industrial agglomeration in our sample. This result is relevant to the transformational market economy, the degree of utilization of high-tech industries, the management of innovation organizations and so on.

Fourth, it should be noted that the synergistic effect between industrial agglomeration and university-industry collaboration on patent output is negative and significant, showing that there are problems and difficulties in managing industrial agglomeration and university-industry collaboration oriented by policy in China’s high-tech industries.

Fifth, FDI has a negative effect on regional patent output, thus suggesting some kind of lack of regional absorptive capacity. Moreover, in view of China as an emerging country and a major recipient of FDI, it may be that foreign direct investment is mainly concentrated in the relatively weak capital and technology intensive industries in the host country, which has obvious competitive advantages, thus excluding domestic enterprises in the host country, resulting in a serious decline in the market share of domestic enterprises.

Sixth, GOV has a negative influence on regional patent output, the reason may be that the higher the government support is, the more it squeezes out regions and enterprises’ investment in research and development. However, regions and enterprises may not develop a good utilization plan and management mechanism for the government support, which results in the ineffective allocation of innovation resources and the decline of innovation output.

Finally, the synergistic effect between FDI and GOV on regional patent output is significantly positive, indicating that only with the support of the government can foreign investment better play the role of knowledge spillover, thus promoting regional technological progress and innovation output. This is because under the subsidy policy, foreign capital is better attracted to technology transfer, promoting the upgrading of domestic industries, and improving the innovation and competitiveness of products.

The main contributions of this study are two-fold: first, combining new economic geography and open innovation theory, we propose an integrated framework from the perspective of innovation knowledge. This integrated framework enables us to consider the geographical location characteristics and spatial heterogeneity, surpass traditional closed innovation system, and identify the impacts of industrial agglomeration, university-industrial collaboration, foreign direct investment and government support on patent output in an open and efficient innovation environment. In particular, we focus on developing countries, where supporting the development of high-tech industries, enhancing innovation and improving innovation capabilities are priorities for government policy [81]. Based on previous micro level studies focusing on developed countries (e.g. [24], [48]), our comprehensive framework helps to capture the driving force of innovation activities from the meso-level, thereby adding a new dimension to the factors affecting the innovation performance of high-tech industries in developing countries.

Second, this study addresses an important gap in the existing literature where empirical evidence on the relationships between industrial agglomeration, university-industrial collaboration, foreign direct investment, government support and patent output is limited [82], [24]. The findings offer valuable empirical evidence on what determines patent output in the first place. It also extends existing studies (e.g. [25], [26]) by examining the negative synergistic effect of industrial agglomeration and university-industrial collaboration, the positive synergistic effect of foreign direct investment and government support on the patent output in the context of open innovation. Therefore, our research provides a more complete description of the mechanism influencing on innovation performance.

Selecting data from different countries to conduct comparisons and discuss reasons is the main future research direction. Because the integrated framework proposed in our research can be used for many objects, this research plays a guiding role to some extent in analyzing other kinds of industries in other countries. At the same time, we hope to bring the effect of spatial spillover into the research, improve the existing models, and achieve a complete interpretation of the promotion of innovation issues on aspects of theory and practice, thus making the study more focused.

REFERENCES

[1] S. Pancholi, T. Yigitcanlar, and M. Guaralda, “Place making facilitators of knowledge and innovation spaces: Insights from European best practices,” Int. J. Knowl.-Based Develop., vol. 6, no. 3, pp. 215–240, 2015.
[2] T. Yigitcanlar, J. Sabatini-Marques, E. M. da-Costa, M. Kamruzzaman, and G. Ioppolo, “Stimulating technological innovation through incentives: Perceptions of Australian and Brazilian firms,” Technol. Forecasting Social Change, vol. 102, pp. 80–89.
[3] X. Li and G. Wu, “In-house R&D, technology purchase and innovation: Empirical evidences from Chinese hi-tech industries, 1995-2004,” Int. J. Technol. Manage., vol. 51, nos. 2–5, 217-238, 2010.
[4] X. Li and T. Buck, “Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries,” Res. Policy, vol. 51, pp. 217–238, Apr. 2010.
[5] S. Klepper, “The origin and growth of industry clusters: The making of silicon valley and detroit,” J. Urban Econ., vol. 67, no. 1, pp. 15–32, Jan. 2010.
[6] J. Wonglilipiyarat, “Exploring strategic venture capital financing with silicon valley style,” Technol. Forecasting Social Change, vol. 102, pp. 80–89, Jan. 2016.
[7] D. Mingullo, R. Tijssen, and M. Thelwall, “Do science parks promote research and technology? A sciento metrics analysis of the UK,” Sociometrics, vol. 102, no. 1, pp. 701–725, Jan. 2015.

[8] F. C. C. Koh, W. T. H. Koh, and F. T. Tschang, “An analytical framework for science parks and technology districts with an application to singa pore,” P. R. T. Dalcol, "Geographical proximity and innovation: Evidence from the Campos Basin oil&gas industrial agglomeration—Brazil," Technovation, vol. 29, pp. 456–461, May 2009.

[9] C.-L. Chang and L. Orley, “Industrial agglomeration, geographic innovation and total factor productivity: The case of taiwan,” Math. Comput. Simul., vol. 79, no. 9, pp. 2787–2796, May 2009.

[10] H. Chesbrough, “Open innovation, the new imperative for creating and profiting from technology,” Harvard Bus. School Press, Boston, MA, USA, Tech. Rep. 1, 2003.

[11] H. Chesbrough, W. Vanhaverbeke, and J. West, Open Innovation: Researching a New Paradigm. Boston, MA, USA: Oxford Univ. Press, 2006.

[12] R. Rauter, D. Globocnik, E. Perl-Vorbach, and R. J. Baumgartner, “Open innovation and its effects on economic and sustainability innovation performance,” J. Innov. Knowl., vol. 78, pp. 8–16, Oct. 2018.

[13] G. G. Dess and J. D. Shaw, “Voluntary turnover, social capital, and organizational performance,” Acad. Manage. Rev., vol. 26, pp. 446–456, Jul. 2001.

[14] M. Harvey and B. S. Tether, “Analysing distributed processes of provision and innovation,” Ind. Corporate Change, vol. 12, pp. 1125–1155, Dec. 2003.

[15] M. Lehrer, P. Nei, and L. Garber, “A national systems view of university entrepreneurship: Inferences from comparison of the German and US experience,” Res. Policy, vol. 38, pp. 268–280, Mar. 2009.

[16] E. B-Y and K. Lee, “Determinants of industry-academy linkages and, their impact on firm performance: The case of Korea as a latecomer in industrial clusters: The case of some italian districts,” J. Econ. Geography, vol. 10, no. 2, pp. 231–255, Mar. 2010.

[17] H. Löff and A. Heshmati, “Knowledge capital and performance heterogeneity: A firm-level innovation study,” Int. J. Prod. Econ., vol. 76, no. 1, pp. 61–85, 2002.

[18] R. Belderbos, M. Carree, and B. Lokshin, “Cooperative R&D and firm performance,” Res. Policy, vol. 33, pp. 1477–1492, Dec. 2004.

[19] A. Scandura, “University-industry collaboration and firms’ R&D effort,” Res. Policy, vol. 45, pp. 1907–1922, Nov. 2016.

[20] Y. Baba, N. Shichijio, and S. R. Sedinta, “How do collaborations with universities affect firms’ innovative performance? The role of ‘Pasture scientists’ in the advanced materials field,” Res. Policy, vol. 38, pp. 756–764, Jun. 2009.

[21] N. Yowl and K. Lee, “Determinants of industry-academy linkages and, their impact on firm performance: The case of Korea as a latecomer in knowledge industrialization,” Res. Policy, vol. 39, pp. 625–639, Jun. 2010.

[22] P. Piperosopoulos, J. Wu, and C. Wang, “Outward FDI, location choices and innovation performance of emerging market enterprises,” Res. Policy, vol. 47, no. 1, pp. 232–240, Feb. 2018.

[23] K.-Y. Cheung and P. Lin, “Spillover effects of FDI on innovation in China: Evidence from the provincial data,” China Econ. Rev., vol. 56, no. 2, pp. 895–906, 2016.

[24] A. Ascani, P.-A. Ballard, and A. Morrison, “Heterogeneous foreign direct investment and local innovation in Italian Provinces,” Struct. Change Econ. Dyn., vol. 53, pp. 388–401, Jun. 2020.

[25] C. Y. W. Lo and A. Wu, “Geographical FDI knowledge spillover and innovation of indigenous firms in China,” Int. Bus. Rev., vol. 25, no. 4, pp. 895–906, 2016.

[26] R. Nelson and E. Phelps, “Investment in humans, technological diffusion, and economic growth,” Amer. Econ. Rev., vol. 56, no. 2, pp. 69–75, 1966.

[27] K. Arrow, Economic Welfare and the Allocation of Resources for Invention. Princeton, NJ, USA: Princeton Univ. Press, 1962, pp. 609–629.

[28] C. Freeman, “Technology, policy and economic performance: Lessons from Japan,” R&D Manage., vol. 19, no. 3, pp. 278–279, 2010.
B. Sun et al.: Industrial Agglomeration, University-Industry Collaboration and Patent Output

[59] R. Nelson, *National Innovation Systems: A Comparative Analysis*. London, U.K.: Oxford Univ. Press, 1993, pp. 839–842.

[60] P. M. Romer, “Endogenous technological change,” *J. Political Econ.*, vol. 98, no. 5, pp. 71–102, 1990.

[61] G. M. Grossman and E. Helpman, *Innovation and Growth in the Global Economy*. Cambridge, MA, USA: MIT Press, 1993, pp. 323–324.

[62] S. Doh and B. Kim, “Government support for SME innovations in the regional industries: The case of government financial support program in South Korea,” *Res. Policy*, vol. 43, no. 9, pp. 1557–1569, 2014.

[63] K.-N. Kang and H. Park, “Influence of government R&D support and inter-firm collaborations on innovation in Korean biotechnology SMEs,” *Technovation*, vol. 32, no. 1, pp. 68–78, 2012.

[64] A. Catozzezza and M. Vivarelli, “The possible adverse impact of innovation subsidies: Some evidence from Italy,” *Int. Entrepreneurship Manage. J.*, vol. 12, no. 2, pp. 351–368, 2014.

[65] B. Lin and R. Luan, “Are government subsidies effective in improving innovation efficiency? Based on the research of China’s wind power industry,” *Sci Total Environ*, vol. 710, Mar. 2020, Art. no. 136339.

[66] Z. Griliches, “Issues in assessing the contribution of research and development to productivity growth,” *Bell J. Econ.*, vol. 10, pp. 92–116, Apr. 1979.

[67] A. Jaffe, “Technological opportunity and spillovers of R&D: Evidence from firms’ patents, profits and market value,” *Amer. Econ. Rev.*, vol. 76, pp. 984–1001, May 1986.

[68] D. C. Guerrero and M. A. Sero, “Spatial distribution of patents in Spain: Determining factors and consequences on regional development,” *Regional Stud.*, vol. 31, no. 4, pp. 381–390, Jun. 1997.

[69] Z. J. Acs, L. Anselin, and A. Varga, “Patents and innovation counts as measures of regional production of new knowledge,” *Res. Policy*, vol. 31, no. 7, pp. 1069–1085, Sep. 2002.

[70] U. Kaiser, H. C. Kongsted, and T. Rønde, “Does the mobility of R&D labor increase innovation?” *J. Econ. Behav. Org.*, vol. 110, pp. 91–105, Dec. 2015.

[71] M. Eshtehardi, S. K. Bagheri, and A. D. Minin, “Regional innovative behavior: Evidence from Iran,” *Technol. Forecasting Social Change*, vol. 122, pp. 128–138, May 2017.

[72] R. Zhang, B. Sun, and M. Liu, “Do external technology sourcing and industrial agglomeration successfully facilitate an increase in the innovation performance of high-tech industries in China?” *IEEE Access*, vol. 7, pp. 15414–15423, 2019.

[73] A. Muscio, D. Quaglione, and M. Scarpinato, “The effects of universities’ proximity to industrial districts on university–industry collaboration,” *China Econ. Rev.*, vol. 23, no. 3, pp. 639–650, Sep. 2012.

[74] S. Blazsek and A. Escribano, “Patent propensity, R&D and market competition: Dynamic spillovers of innovation leaders and followers,” *J. Econometrics*, vol. 191, pp. 145–163, Mar. 2016.

[75] J. C. Driscoll and A. C. Kraay, “Consistent covariance matrix estimation with spatially dependent panel data,” *Rev. Econ. Stat.*, vol. 80, no. 4, pp. 549–560, Nov. 1998.

[76] S. Charlton, R. Crescenzi, and A. Musolesi, “Econometric modelling of the regional knowledge production function in Europe,” *J. Econ. Geography*, vol. 15, no. 6, pp. 1227–1259, Nov. 2015.

[77] H.-L. Lin, H.-Y. Li, and C.-H. Yang, “Agglomeration and productivity: Firm-level evidence from China’s textile industry,” *China Econ. Rev.*, vol. 22, no. 3, pp. 313–329, Sep. 2011.

[78] A. MacPherson, “The role of producer service outsourcing in the innovation performance of new york state manufacturing firms,” *Ann. Assoc. Amer. Geographers*, vol. 87, no. 1, pp. 52–71, Mar. 1997.

[79] J. H. Love and S. Roper, “Outsourcing in the innovation process: Local and strategic determinants,” *Papers Regional Sci.*, vol. 80, no. 3, pp. 317–336, Jan. 2005.

[80] M. Perkmann, V. Tartari, M. McKelvey, E. Autio, A. Broström, P. D’Este, R. Fini, A. Geuna, R. Grimaldi, A. Hughes, S. Krabel, M. Kitson, P. Llerena, F. Lissoni, A. Salt, and M. Sobrero, “Academic engagement and commercialisation: A review of the literature on university–industry relations,” *Res. Policy*, vol. 42, no. 2, pp. 423–442, Mar. 2013.

[81] F.-C. Liu, D. F. Simon, Y.-T. Sun, and C. Cao, “China’s innovation policies: Evolution, institutional structure, and trajectory,” *Res. Policy*, vol. 40, no. 7, pp. 917–931, Sep. 2011.

[82] D. Fornahl and T. Brenner, “Geographic concentration of innovative activities in Germany,” *Struct. Change Econ. Dyn.*, vol. 20, no. 3, pp. 163–182, Sep. 2009.

BING SUN received the Ph.D. degree from the School of Economics and Management, Harbin Engineering University, Harbin, China, in 2003. She is currently a Professor and a Ph.D. Supervisor with the School of Economics and Management, Harbin Engineering University. She has presided more than ten national and provincial research projects, published more than 100 academic articles in journals, and two academic publications. Her research interests include technological innovation and technology diffusion. She received the New Century Excellent Talent by the Chinese Ministry of Education in 2010.

RUIHAN ZHANG is currently pursuing the Ph.D. degree with the School of Economics and Management, Harbin Engineering University, Harbin, China. She was a Visiting Student with the Haas School of Business, Institute for Business Innovation, University of California at Berkeley, Berkeley, USA, from 2018 to 2019, supervised by Prof. David J. Teece and supported by the China Scholarship Council (CSC). Her research interests include innovation management, technology management, dynamic capabilities, cooperation, and technology evolution in high-technology industries. During her studies, she has participated in research work of the National Natural Science Fund Projects and Provincial Social Science Fund Project of China and done international conference presentations in China and USA.

HONGYING MAO received the M.S. degree from the School of Economics and Management, Harbin Engineering University, Harbin, China, in 2015, where she is currently pursuing the Ph.D. degree. Her research interests include technology innovation and information management.

***