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Exploring the Spatially-Varying Effects of Human Capital on Urban Innovation in China

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Abstract
This study employs city-level data from China to examine the spatially-varying effects of human capital on urban innovation, applying the multi-scale geographically weighted regression model to the knowledge production function. The results demonstrate that the effects of various determinants-including human capital, industrial structures, research and development investment, environmental quality, economic development levels-on innovation prompt different spatial patterns and ranges of influence, among which human capital significantly enhances the level of innovation with the strongest scale effects. Hence different policies should be formulated in cities of diverse conditions that are sensitive to their contexts.

Keywords Human capital · Innovation · Spatially-varying effects · Multi-scale geographically weighted regression · Knowledge production function

Introduction

In the contexts of economic globalization and the knowledge economy, innovation has become a major source of competitive advantage and a main driving force of economic development. Since China's economic development has entered its new state – that is to say, since there has been a shift from rapid economic development to medium-to-high speed growth – heated debates have been underway regarding China's economic growth patterns and the factors that drive them. It is generally acknowledged that China's economic growth since the "reform and opening-up" of

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the country in the late 1970s, has mainly been driven by factors such as capital, energy, raw materials, and labor forces, while technical progress and innovation have, in contrast, contributed little to the economic growth of the nation (Gu & Liu, 2012). In recent years, as the number of China's factor endowment advantages has gradually decreased in terms of resources, environment, and population, the nature of the country's economic growth has begun to transform from the traditional factor-driven and investment-driven patterns to the new innovation-driven patterns that rely on technological progress to improve the rates of productivity (Tao & Peng, 2018). In the meantime, the Chinese government has proposed the adoption of an innovation-driven national development strategy and has set a target to situate China at the forefront of innovative countries worldwide. Such sources of innovation involve the inputs of physical capital and human capital, as well as social environment and government policies. Human capital – an essential resource for, as well as a significant driver of, innovation – has captured the full attention of society (Cai, 2014).

From a realistic perspective, China has become a great force of human capital despite still not having secured the status of being a great power of innovation (Gu et al., 2019). In 2018, there were 38.3 million students enrolled in higher education in China, which ranked first in the world. The gross enrollment rate in higher education in China in 2018 was 48.1%, indicating that the sector is about to transform from the massification stage into the popularization stage (Liu & Gu, 2020). In addition, China also has the largest number of research and development personnel (cited as 4.1 million individuals in 2018) in the world.

However, the high volume of human capital in China does not guarantee high returns on innovation. China only ranked the 17th place in the World Intellectual Property Organization ("WIPO") Global Innovation Index ("GII") of 2018, climbing five spots from the previous year's index (2017) in which China ranked the 22nd. Although China has already made significant achievements in the field of innovation, a huge gap still exists between China and developed countries, such as the United States, the countries of the European Union, and Japan. As China is a large country that has a vast territory, it experiences pronounced levels of regional disparity in innovation (Fang et al., 2014; Wang & Xu, 2016). In 2017, the region that had the highest levels of innovation (Beijing) was 40 times more successful in this context than the region that had the lowest levels of innovation (Tibet), as signaled by the number of patents granted per capita. Since innovation capacity is a crucial impetus for regional economic development, the widening regional disparity in innovation capacities will lead to the enlargement of the regional development gap, thus causing widespread public concern (Zeng et al., 2019).

As the key to the success of innovation, "human capital" refers to a stock of knowledge, skill, ability, physical strength (being in good health), and personality that can be used to produce economic value. In such contexts, it is wise for nations to invest in human capital through education, training, practice, and migration to ensure that they are essential sources of competitive advantage to individuals, firms, and regions (Kaasa, 2009). Generally speaking, innovation and human capital can be both divided into two levels: the firm level and the regional level (Jang et al., 2017; Sun et al., 2020; Wang & Lin, 2013). Though studies into innovation at the firm level are critical, studies on regional innovation are also of great concern, due to the need for policies to address regional inequalities in accordance with the evidence that innovation is a source of competitive advantage (Asheim et al., 2011).

As spatial data, information about regional human capital and innovation includes a series of site and situational attributes that are based on the location and may exhibit spatial effects, including spatial dependence (similarities in position) and spatial heterogeneity (the tendency for the relationships among variables to vary across space), which violate the classic assumptions of non-spatial regression methods (such as ordinary least squares or "OLS") and cause estimate bias (Jang & Kim, 2018; Kim et al., 2020). Although there is already a large and burgeoning body of literature on the relationship between regional human capital and innovation (Castellacci & Natera, 2013; Dakhli & De Clercq, 2004; Faggian & McCann, 2009; Kaasa, 2009; Lee et al., 2010), only a few studies hitherto have paid attention to the spatial dependence (Marrocu et al., 2013; Qian et al., 2010; Zhang & Shi, 2018) – not to mention the spatial heterogeneity – of this relationship. Nevertheless, regional and urban studies have demonstrated the existence of spatially-varying agglomeration effects (Cheng & Li, 2011; Shearmur, 2012; Kang & Dall'erba, 2016). There is a vast disparity in the levels of innovation across different regions due to them having varied regional characteristics. Consequently, it may be that different contextual influences cause the spatial variations in the relationship between the levels of regional innovation and their determinants, which can further provide support for location-based practical innovation strategies when combined with visualized maps (Jang et al., 2017).

Therefore, to rectify the deficiencies of extant studies – based on the data of Chinese prefecture-level cities – in this study, we will employ a spatial econometric method to investigate the underlying spatial variations in modeling urban innovation, thus providing empirical evidence for local governments on how they should formulate and adopt customized innovation strategies in response to China's transition from a human capital powerhouse to an innovation powerhouse, as well as foreground the country's need to narrow the huge gap in regional innovation capabilities. Specifically, we will address the following research questions:

(1) How, and to what extent, has human capital affected innovation capacities at the city level in China?

(2) How do cities differ in the effects of human capital on innovation?

Regarding its international meaning, this study provides not only academic evidence for the influence mechanism of human capital on innovation with the typical case of China, which has the largest human capital investments and relatively lower innovation outputs, but also practical references for other developing countries facing similar situations, in the economic transformation from the factor-driven and investment-driven pattern to the innovation-driven pattern.

The paper is structured as follows. In the second section, we conduct a comprehensive literature review. Then, in the third section, we provide details about both the data and the chosen methodology. In the fourth section, we undertake an analysis of the research results before offering concluding comments in the final section.

Literature Review

From the theoretical perspective of human capital and innovation, Schultz (1960) has stated that the economic development of a nation is primarily contingent upon the accumulation of human capital; the rate of return on investment in human capital is considerably high. Becker (1964) contributes to the microeconomic analysis of human capital, by elaborating on different kinds of investments that are intrinsic to the formation of human capital (such as education and training) and their revenues. Regional innovation system theories – drawing on the literature on industrial districts, clusters and innovative milieu – emphasize the significance of economic and social interactions between agents and the roles of both the public and private sectors in generating and disseminating innovative practices both within and across regions. Indeed, such theories regard the accumulation of human capital as being the key component of the innovation process in regions (Asheim & Gertler, 2005). Marshall (1890) was among the first economists who investigated the role of innovation from a regional perspective. By focusing on industrial districts and innovation, he formulated the concepts of internal economies of scale and external economies. According to the endogenous growth theory, human capital is deemed as an endogenous variable to promote economic growth through technical innovation, including two kinds of views. One view is the capital-driven pattern that has been put forward by Romer (1986, 1987) – i.e., that the externalities caused by human capital and physical capital advance technical innovation, thus promoting economic growth – while the other perspective is that technical innovation is independently driven by the research and development ("R&D") sector and based on human capital investment (Grossman & Helpman, 1991).

From the empirical perspective, a considerable body of literature explores the various factors that affect the innovation capacity of a region. Research and development(R&D) investments – including expenditure and personnel – contribute traditional inputs to the knowledge production function of innovation (Cohen, 1995); their positive effects on regional innovation capacities have been demonstrated by a series of studies (Bottazzi & Peri, 2003; Crescenzi et al., 2012; Fritsch & Franke, 2004; Fritsch & Slavtchev, 2011; Wang & Kafouros, 2009). Securing foreign direct investment(FDI) has long been one of the most well-known approaches that are used to drive innovation through which firms and industries can obtain access to advanced knowledge and technology (Crespo & Fontoura, 2007; Fu et al., 2011). Therefore, developing countries can benefit significantly from FDI due to its role in transferring production expertise and managerial skills as well as producing spillover effects (Balasubramanyam et al., 1996; Chen, 2007; Chen et al., 2017; Huang et al., 2012). Research and development(R&D) investments and foreign direct investment(FDI) are the main drivers for regional innovation in China; they are both closely associated with human capital. Human capital is one of the principal factors that influence the input–output performance of R&D capital when considering the effects of R&D investments on technological innovation (Li et al., 2007), because having a larger stock of national human capital means having a stronger capacity to absorb and to utilize advanced foreign science and technology, and to exercise independent innovation. As the level of human capital determines a nation's capability to adopt foreign techniques, countries may need to ensure that they have a certain level of human capital to experience the positive effects of FDI (Borensztein et al., 1998). Hence, human capital is also a crucial determinant in fostering innovation (Huang et al., 2012; Li et al., 2007; Ning et al., 2016).

Besides, regions can differ in their resources and abilities as well as – most importantly – in the externalities of industrial agglomeration in enhancing levels of knowledge and economic growth (Ning et al., 2016). A variety of regional characteristics are related to innovation: social capital(Dakhli & De Clercq, 2004; Maillat, 1998), industrial characteristics(Lee et al., 2010), diversity(Lee, 2015; Niebuhr, 2010), infrastructure construction (Crescenzi et al., 2012; Lee et al., 2010), economic development level (Chen, 2007; Cheung & Ping, 2004), and so on.

Since innovation is knowledge-based, it is inseparable from human capital good at harnessing knowledge and technology in many ways. Many studies have identified the importance of human capital in promoting innovation at the regional level (Castellacci & Natera, 2013; Dakhli & De Clercq, 2004; Faggian & McCann, 2009; Kaasa, 2009; Lee et al., 2010; Makkonen & Inkinen, 2013; Marrocu et al., 2013). Accordingly, there is a growing body of literature on human capital and innovation at the subnational level in China, among which most studies focus on the provincial level (Cheung & Ping, 2004; Wu, 2011; Crescenzi et al., 2012; Huang et al., 2012; Chen et al., 2017; Zhang et al., 2018; Gu et al., 2020a), whereas few studies pay attention to the city level. The provincial analyses (Chi & Qian, 2010; Fleisher et al., 2010; Qian et al., 2010; Crescenzi et al., 2012, 2017) may provide some evidence for China's regional innovation system, but urban heterogeneity and interregional externalities within provinces have been neglected (Ning et al., 2016). The reason is that China is a country with a vast territory, and some of its provinces are even larger than some European countries.

Studies of cities and regional growth have suggested that cities operate as collectors of human capital to spur innovation and economic growth, and the role of cities has been well documented (Gu et al., 2020b; Park, 2019; Jacobs, 1969; Lucas, 1988; Glaeser, 2011; Shearmur, 2012; Tukiainen et al., 2015). Consequently, some related studies at the city level in China begin to emerge. Han et al. (2010) found that urban economic strength, urbanization levels, foreign direct investments, talents, and educational levels are determinants of city innovation, based on evidence from 21 prefecture-level cities in Guangdong Province from 1994 to 2007. Using panel data of Chinese prefecture-level cities, Gao (2015) examined the effects of city sizes and human capital on innovation capacities and the interaction effects between human capital and city sizes. Ning et al. (2016) investigated the spatial effects of both FDI spillovers and industrial agglomeration – as well as their interaction with urban innovation – by using the spatial econometric models to consider both the intraregional and interregional spatial externalities of FDI, based on a dataset of 181 Chinese cities from 2005 to 2011. Using panel data of 283 cities from 2003 to 2014, Rodríguez-Pose and Zhang (2019) demonstrated that the urban growth in China is driven by human capital, innovation, density, local conditions, foreign direct investment and city-level government institutions. Wang (2019) employed city-level data of China in 2010 to examine the direct effect of a city's government capacity on its economic growth, considering the role of human capital.

It is well known that spatial variation exists in the context of the innovation capabilities of different regions (Kang & Dall'erba, 2016). The reason for such variation is that a region's innovative capacity is subject to local conditions such as its geographical factors, the quality of its institutions, and the level of agents' interactions within the region (Agrawal et al., 2010). Since the regional conditions are heterogeneous over space, one should expect that the mechanisms of regional innovation also vary spatially, especially the effect of the crucial factor: human capital.

However, among the studies on the influences of human capital on innovation, relatively few studies have paid attention to the spatial effects. Kang and Dall'erba (2016) examined the spatial heterogeneity in the marginal effects of knowledge input factors (including human capital) on the knowledge output (patents) using GWR and mixed GWR models, with two distinct samples of the United States Metropolitan Statistical Area ("MSA") and non-MSA counties. Marrocu et al. (2013) employed the spatial autoregressive model ("SAR") and the spatial Durbin model (SDM) to analyze the role of internal factors (human capital and R&D) and external factors (interregional proximity and connectivity) in promoting innovation at the regional level. They found that a considerable portion of the total effects of R&D investments and human capital on innovation in a particular region derives from the spatial spillover effects that result from other regions. Some scholars (Qian et al., 2010; Zhang & Shi, 2018; Zhu & Zheng, 2018) have employed spatial econometric models to investigate the impact of human capital on innovation and its spatial spillover effect by using China's provincial panel data.

In conclusion, the theoretical studies discuss the relationship between human capital, innovation, and economic growth from the microeconomic perspective, concerning the levels of individuals and industries instead of regions. Some scholars do mention the externalities of human capital (Jacobs, 1969; Lucas, 1988; Marshall, 1890), while lacking the analysis of spatial effects. Similarly, the empirical studies have afforded much attention to the effects of human capital on regional innovation, and yet there has been a deficiency in the research on the spatial variation of these effects. As cities are important collectors of human capital to promote innovation, this study will extend the prior literature by not only identifying the spatially-varying relationship between human capital and innovation at the city level using spatial econometric methods but also contributing to the more effective place-tailored innovation policies.

Data and Methodology

Model and Variable Selection

Regional knowledge production function (KPF, Griliches, 1979) is usually used to estimate the influences of different factors on regional innovation systems, which claim that the innovation output is related to the knowledge stock and human capital inputs (Audretsch & Feldman, 2004). In addition, other determinants influence the aforementioned regional innovation activities. According to the extant literature and the limited data available, we have selected a series of variables to be incorporated into our empirical model of regional knowledge production function as shown below:

$$PATENT_i + \beta_0 + \beta_1 EDU_i + \beta_2 SINDUS_i + \beta_3 TINDUS_i + \beta_4 FDI_i + \beta_5 EXP_i + \beta_6 EMP_i + \beta_7 GREEN_i + \beta_8 EMI_i + \beta_9 WAGE_i + \varepsilon_i \tag{1}$$

Where $PATENT_i$ is the dependent variable-innovation, EDU_i is the independent variable-human capital, the other variables are control variables, ε_i is the error term. The variables shown in Eq. (1) are explained in detail below.

In this study, we regard prefecture-level cities in China as subjects, with the subscript variable i referring to each city since cities act as collectors of human capital to foster innovation. The dependent variable (knowledge output) is measured by the average number of total patents granted per 10 thousand people in city i($PATENT_i$). Though there are a lot of measures to capture innovation(Goetz & Han, 2020), the number of patents granted is a prevalent indicator to evaluate innovation (Chen & Puttitanun, 2005; Tebaldi & Elmslie, 2013) for the following reasons: patents represent new ideas, new products, and new technology, and are closely related to technical innovation; it covers nearly all of the fields of technology, thus providing a homogeneous measure for all countries; many countries have established their patent databases, making the patent data possess time seriality and comparability (Lee et al., 2010). The number of total patents is composed of the number of granted patents for invention, utility model, and appearance design, which is relatively representative, systematic, and accessible. The patent data is derived from China's patent full-text database of 2016, issued by National Intellectual Property Administration, PRC.

Regarding the index selection for the independent variable, measures for human capital incorporate educational attainment levels, average years of schooling, school enrollment rates, students' international test scores, and the monetary value of the human capital stock (Teixeira, 2005). In China, human capital is closely related to formal education, so we use the average years of schooling of the labor force in city i (EDU_i) to measure it, which is collected from the 1% national population sampling survey data of 2015.[1]

According to the literature review that has been presented in the previous section, the other variables that influence innovation include research and development investment, FDI, industrial characteristics, and economic development levels. The R&D investment is captured by using the public finance expenditure on science and education in city *i* (EXP_i). We use the amount of foreign capital utilized to proxy foreign direct investment (FDI_i). The industrial characteristic is measured by the proportion of secondary industry output value to GDP ($SINDUS_i$) and the proportion of tertiary industry output value to GDP($TINDUS_i$). We employ the average

[1] Data sources: the microeconomic survey data of China's National Bureau of Statistics obtained from Tsinghua China Data Center (CDC). Disclaimer: This research results do not present opinions of China's National Bureau of Statistics or CDC.

Table 1 Descriptive statistical analysis

Variables	Obs	Mean	Std. Dev	Min	Max
PATENT	288	5.294208	11.13628	0.0104983	106.4255
EDU	288	9.965278	0.819307	7.1	12.7
WAGE*	288	53,910.52	11,351.6	4958	114,582
FDI*	288	580,671.1	1,393,220	641.5252	13,200,000
SINDUS	288	46.60149	9.554485	15.17	71.45
TINDUS	288	41.03111	8.766079	24.17	79.65
EXP*	288	792,267.3	1,081,450	73,421	11,400,000
EMI*	288	49,203.21	42,455.6	208	426,800
GREEN	288	48.31182	49.39345	0.2404389	424.3372
EMP*	288	642,314.1	1,009,348	65,550	9,868,700

*represents natural logarithm transformation

annual wage of employed staff and workers ($WAGE_i$) to proxy the economic development level of each city. It is expected that cities that demonstrate better environmental quality are more attractive to talents, thus generating higher yields of innovation output (Glaeser et al., 2001). Therefore, we control for the urban environmental factors by using the area of green space per capita ($GREEN_i$) and the volume of sulfur dioxide emission (EMI_i). We also control for the urban population size with the employment figure of city i (EMP_i), as it signifies the labor input in the traditional knowledge production function.

The descriptive statistical analysis of the aforementioned variables is shown in Table 1. The number of patents granted comes from China's patent full-text database of 2016, the average schooling years of the labor force are collected from the 1% national population sampling survey data of 2015, and the other variables are gathered from the *China City Statistical Yearbook 2016,* which reflects the socioeconomic conditions of Chinese cities in 2015. Therefore, the dependent variable is one-period lagged from the independent and control variables, which facilitates the mitigation of the endogeneity in the model (Gu et al., 2019). Due to the data accessibility, our data includes 288 prefecture-level cities of China in 2015.

Multi-Scale Geographically Weighted Regression (MGWR)

We could use the ordinary least square ("OLS") – a classic global model – to regress these variables on the number of patents per capita. However, though a global model controls major variables, it cannot provide us with more details about the spatial variances. As there is a remarkable spatial disparity in human capital, economic development levels, and environmental quality between different cities, their influencing effects on innovation could also vary across space, which is called the spatial non-stationarity. However, global models cannot capture the spatial non-stationarity, thus resulting in the widespread use of local models.

Among local models, geographically-weighted regression (GWR) is a useful model with which to detect spatial non-stationarity. GWR is a local regression technique that estimates parameters by borrowing data from nearby sampling points (Brunsdon et al., 1996; Fotheringham et al., 2003). The bandwidth in the GWR model is the average of different bandwidths of all explanatory variables, which will cause model bias and unnecessary noises (Gu et al., 2021). The multi-scale geographically weighted regression ("MGWR"), as the latest improvement of GWR, can remedy this defect by taking into consideration the varying bandwidths of different independent variables (Fotheringham et al., 2017; Yu et al., 2019). As a better fitting model, MGWR can tell us the unique scale of each variable. In this study, because of the existence of spatial heterogeneity, the effects of explanatory variables may vary across space and in different scales, among which the influencing range of human capital on urban innovation is of the greatest significance (Lao & Gu, 2020). Therefore, we have employed the MGWR to detect the spatially-varying effects in this study.

An MGWR model is formulated as

$$y_i = \sum_{j=1}^{k} \beta_{ij} \chi_{ij} + \varepsilon_i \tag{2}$$

where for the observation at location $i \in \{1, 2, \ldots, n\}$, y_i is the response variable, x_{ij} is the j th predictor variable,$j \in \{1, 2, \ldots, k\}$, β_{ij} is the j th parameter estimate, and ε_i is the error term. MGWR can also be expressed as a Generalized Additive Model (GAM) format:

$$y = \sum_{j=1}^{k} f_j + \varepsilon \tag{3}$$

where $\boldsymbol{f_j}$ is a smooth function applied to the j th predictor variable. In the context of MGWR, each smooth function $\boldsymbol{f_j}$ is a spatial GWR parameter surface that is calibrated by using a known bandwidth. This bandwidth can be varying over j in MGWR. The estimation and inference processes of MGWR are demonstrated in Fotheringham et al. (2017) and Yu et al. (2019).

To calculate the optimal bandwidth, the adaptive bi-square kernel function (Fortheringham et al., 2017) is employed, with the back-fitting algorithm using the residual sum of squares(RRS):

$$SOC_{RSS} = \left| \frac{RSS_{new} - RSS_{old}}{RSS_{new}} \right| \tag{4}$$

where $\mathrm{SOC}_{\mathrm{RSS}}$represents the convergence criterion, $\mathrm{RSS}_{\mathrm{new}}$ signifies the RSS in the last step's calculation, and $\mathrm{RSS}_{\mathrm{old}}$ stands for the RRS in the next step's calculation.

The criteria to select the optimal bandwidth in MGWR is the corrected Akaike information criteria(AICc), which can be represented as:

$$AICc = 2n \ln(\sigma) + n \ln(2\pi) + n \frac{n + tr(S)}{n - 2 - tr(S)} \tag{5}$$

where n signifies the number of observations, σ denotes the standard deviation of residuals, and tr(S) represents the trace of the hat matrix in MGWR.

The unit of bandwidth in MGWR is the number of sampling points surrounding the regression point, which has impacts on the regression coefficients. In this study, the unit of bandwidth signifies the number of cities, indicating the influencing range of a certain variable.

Results

Model Processing

This section begins with the results of the OLS, GWR, and MGWR models. To test the multicollinearity in the model, we calculated the variance inflation factor ("VIF") and found that the VIF of each variable is less than 7. The results of the VIF show that there is no multicollinearity in our model. To tackle the possible endogeneity problem that can be caused by reverse causality, our dependent variable is one-period lagged from the independent and control variables. Furthermore, since our analytical framework has accommodated various control variables that may influence the innovation of the city, the endogeneity caused by omitted variables can be addressed to a certain degree.

To evaluate the robustness of the OLS model, we first put the independent variable into the model, followed by models that contain control variables from the aspects of economic, industry, R&D investments, environmental factors, and labor supplies, step by step (Model 1 to Model 6, see Table 2). Considering the possible heteroscedasticity in the model, we use the robust standard error to calculate t statistics and p values. The AICc value of the OLS model decreases when more control variables are introduced into the model, and the R^2 and the adjusted R^2 of the model increase, which indicates that the model-fitting ability has been enhanced by the addition of more control variables.

To examine the spatial variation of the influencing factors, we further construct a GWR model (Model 7) and an MGWR model (Model 8), both of which incorporate all of the independent and control variables. The results of the GWR and MGWR models are shown in Table 3. Since the GWR and MGWR are local regression models, we list the average of the estimates, the average of the t statistics, and the standard deviation of the variables. In general, the R^2 (0.839) and the adjusted R^2 (0.793) of the MGWR model are the highest among all of the models, while its AICc is the lowest (457.934), illustrating that the MGWR model considering spatial non-stationarity and multi-scale bandwidths provides significantly better goodness of fit than other models when assessing the spatially-varying distribution of variables. Particularly, the results imply that there is a significant improvement in the MGWR model when compared with the traditional GWR model.

Table 2 Parameter estimates for the global (OLS) model

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Variables	PATENT	PATENT	PATENT	PATENT	PATENT	PATENT
EDU	6.209***	3.058***	2.111**	2.616***	2.521***	2.317***
	(1.216)	(0.815)	(0.845)	(0.864)	(0.828)	(0.853)
WAGE		12.694**	10.063*	7.265*	5.065	5.222
		(5.908)	(5.345)	(4.227)	(3.322)	(3.412)
FDI		1.714***	1.544***	0.525	0.466	0.395
		(0.395)	(0.349)	(0.337)	(0.300)	(0.338)
SINDUS			0.107	0.102	0.143**	0.141**
			(0.074)	(0.071)	(0.069)	(0.067)
TINDUS			0.283**	0.206*	0.170*	0.167*
			(0.133)	(0.110)	(0.091)	(0.092)
EXP				4.251***	5.578***	4.483***
				(1.273)	(1.511)	(1.509)
EMI					-2.717**	-2.783**
					(1.203)	(1.234)
GREEN					0.052*	0.052*
					(0.030)	(0.030)
EMP						0.940
						(1.409)
Constant	-56.584***	-183.533***	-160.088***	-175.482***	-142.006***	-142.306***
	(11.701)	(64.812)	(26.927)	(46.747)	(34.794)	(35.664)
Obs	288	288	288	288	288	288
R^2	0.209	0.349	0.367	0.408	0.494	0.495
Adj. R2	0.206	0.342	0. 356	0. 396	0.480	0.479
AICc	755.980	703.911	699.934	682.918	641.803	643.524

Standard errors are in parentheses

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively

OLS results

The results of the OLS models exhibit the significant positive effects of human capital on innovation in a city, thereby answering the first research question proposed in the introduction. To be specific, the average schooling years of the labor force of the city (EDU) are positively associated with the number of patents granted per capita (PATENT). Meanwhile, the relationship between human capital and the innovation level of a city is robust, since the variable EDU is statistically significant from Model 1 to Model 6. Moreover, after controlling all factors that may influence the dependent variable (see Model 6), we find that the proportion of secondary industry output value to GDP (SINDUS) and the proportion of tertiary industry output value to GDP (TINDUS) are significant predictors for urban innovation, since innovation activities mostly happen in high-end manufacturing and some tertiary industries, with high technology content

Table 3 Results from the GWR model and MGWR model

	(7) GWR			(8) MGWR		
	PATENT			PATENT		
Variables	β	$\overline{\lvert t \rvert}$	Std. Dev	β	$\overline{\lvert t \rvert}$	Std. Dev
EDU	0.236**	1.973	0.164	0.277**	2.246	0.254
WAGE	0.219*	1.854	0.143	0.225*	1.884	0.173
FDI	0.046	0.922	0.149	0.014***	0.281	0.002
SINDUS	0.190	1.263	0.136	0.150*	1.732	0.285
TINDUS	0.135	0.967	0.114	0.029	0.386	0.005
EXP	0.230	1.295	0.112	0.097	1.149	0.003
EMI	-0.190**	2.061	0.124	-0.148***	2.636	0.072
GREEN	0.110*	1.936	0.177	0.075*	1.648	0.126
EMP	0.021	0.794	0.182	0.093	0.937	0.156
Constant	-0.085	1.222	0.089	-0.138**	2.119	0.088
Obs	288			288		
R^2	0.757			0.839		
Adj. R^2	0.699			0.793		
AICc	550.837			457.934		

β represents the average estimates of variables. $\overline{\lvert t \rvert}$ represents the average t values of variables. Std. Dev. is the standard deviation of variables' coefficients

*, **, and *** denote significance at the 10%, 5% and 1% levels, respectively

and high added value. Besides, the public finance expenditure on science and education (EXP) affects innovation, since it is an essential input for innovation activity.

The two environmental indicators also have significant effects on innovation. The increase in the area of green space per capita (GREEN) and the reduction of the volume of sulfur dioxide emissions (EMI) signify better environmental quality, thus attracting more creative people and promoting innovation in a city. The average annual wage of employed staff and workers (WAGE) represents the economic development level of a city. An economically-developed city will receive more investments in science and technology and will be a more attractive prospect for innovative talents. In Model 1 to Model 4 (see Table 2), the variable WAGE is significant. However, after controlling the effects of urban environmental quality and labor supply, WAGE becomes insignificant. Besides, both the amount of foreign capital utilized (FDI) and the employment figure (EMP) have positive regression coefficients, but they are not significant.

MGWR results

As a local regression analysis, each spatially nonstationary variable at each sample point has its unique R^2, standard error, and t value in the MGWR model. Besides, each variable has its particular bandwidth (influencing range) in an MGWR

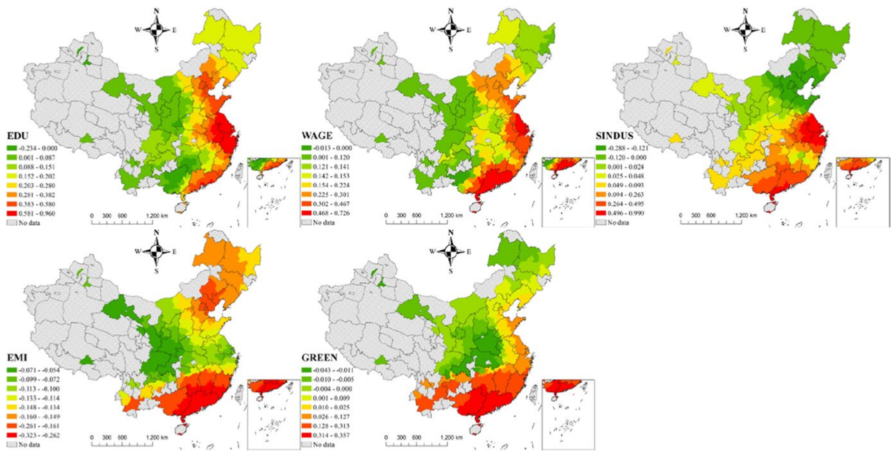

Fig. 1 Spatial patterns of regression coefficients of explanatory variables

specification. To reveal the spatial pattern of spatially nonstationary variables, we have only selected the explanatory variables with statistical significance ($|t| \geq 1.64$) and divided each variable into 8 levels in terms of its degree of influence by using the Jenks classification method: from the highest to the lowest. The significant spatial variance of influencing effects of various variables on innovation – due to the heterogeneous agglomeration effects in regional innovation activities – are revealed in Fig. 1, which addresses the second research question.

In general, the MGWR model results also demonstrate the significant positive impact of human capital on urban innovation. Some significant control variables in the OLS model still corroborate the significance of the MGWR model, including SINDUS, EMI, and GREEN. However, the variables TINDUS and EXP are insignificant in the MGWR model, although some urban economic factors (WAGE and FDI) are significantly positively-related to urban innovation. According to the results of the OLS and MGWR models, the effects of urban economic development, public service supply, and industrial structures are not strongly robust. The significant relationship between human capital and urban innovation is, though, verified.

Supported by the GIS software, the spatial variation patterns of estimators of variables can be further studied (see Fig. 1). Firstly, regarding the independent variable (EDU), the high values of the effects of human capital on innovation are concentrated in the eastern coastal region – especially in the urban agglomerations of the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei – while the low values emerge in the central and western regions. This indicates that the effects of human capital on innovation are spatially nonstationary; the effects of human capital on innovation are stronger in regions where the economies of scale are more developed. Agglomeration economies can increase the likelihood of knowledge spillovers – i.e., human capital externality – thus promoting per capita innovation output. The improvement of human capital can also enlarge the effects of agglomeration economies. The dense concentration of talents in cities will create an environment where the knowledge exchange easily happens among individuals and new ideas travel quickly, thus facilitating knowledge spillover and enhancing innovation and productivity(Carlino & Kerr, 2015). This result supports the emphasis on human capital externality in the economic growth process following the new economic growth theory (Lucas, 1988).

Secondly, concerning the economic indicators, the effects of the average wages of employed staff and workers (WAGE) on innovation show similar characteristics to those that relate to human capital. The high values emerge in eastern coastal cities, with the urban agglomerations of Pearl River Delta and Yangtze River Delta as cores, while central, western, and northeastern regions are areas of low values. The average wage reflects the overall income condition and economic development level, and the wage growth will play a more significant role in spurring innovation in regions with a more developed scale economy, due to the externalities that arise from the agglomeration economy. The effects of the proportion of secondary industry output value to GDP (SINDUS) are much greater in the urban agglomerations of Pearl River Delta and Yangtze River Delta, while they are much lower in northern China, the western region and the northeastern region. The possible reason may be that the urban agglomerations of the Pearl River Delta and Yangtze River Delta, dominated by the second industry, have benefitted from the second industry development as well as the developed and diversified industrial clusters, contributing to the formation of innovation (Guo et al., 2019). The effects of EDU and WAGE are only non-positive in a small part of the Central and Southern China Region(Guangxi and Hunan Provinces), indicating that this region lags relatively in human capital and economic development level, which contributes little to spurring innovation.

Thirdly, regarding environmental indicators, the high negative values of the effects of sulfur dioxide emissions (EMI) on innovation emerge in the southern region of China – including Guangdong, Fujian, Jiangxi, Hunan, and Guangxi – the reason for which is that China's southern region usually has industrial structures that are based on light industry and relatively higher air quality. The increase in the emission volume of sulfur dioxide will constitute a considerable repulsive force to innovative talents, thus sharply decreasing the levels of innovation. Meanwhile, the region in which Beijing and Tianjin are at the core also presents high negative values, which verifies the fact that the recent air quality deterioration in the Beijing-Tianjin-Hebei region is negatively related to the process of trying to attract talented people for innovation production. In addition, the most potent positive effects of the green space area per capita (GREEN) appear in the southern region of China, similar to the matter of sulfur dioxide emissions. Some parts of the eastern coastal region have been identified as having experienced very positive effects, while the weak effects have been seen in central, western, and northeastern regions.

Finally, different variables have different bandwidths in the MGWR model that is shown in Fig. 2, revealing multi-scale effects. We will now discuss the spatial scale of each variable, which reflects the degree of spatial variation in the effect of each influencing factor on urban innovation. Among all variables, human capital(EDU) has the smallest bandwidth of 47 cities, indicating that the spatial influence of human capital on innovation is confined to a cluster consisting of 47 cities and that the spatial relationship between human capital and innovation will show dramatic variability beyond the

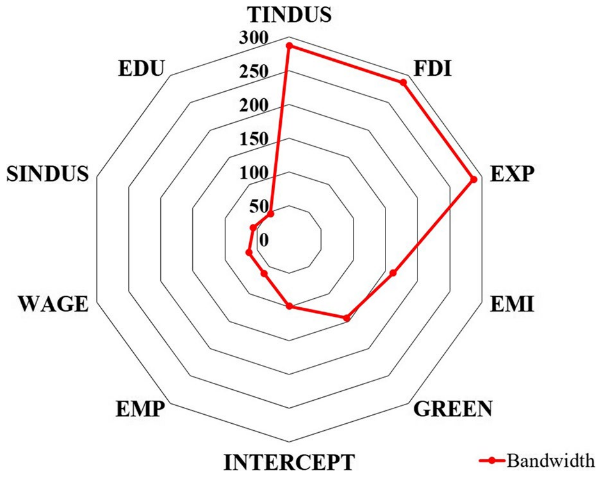

Fig. 2 Bandwidths for explanatory variables in MGWR

spatial range of this cluster. The spatial variation of the estimator of human capital is very remarkable; the geographical location seems to matter a great deal. The possible reason for this may be that the distribution of highly-educated people and talents is very uneven, and they are mainly concentrated in metropolitan areas, such as the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei urban agglomerations; there is a cornucopia of employment opportunities and public services in these regions, thus generating stronger effects of agglomeration economies. Similarly to human capital, the economic indicators – the proportion of secondary industry output value to GDP (SINDUS) and the average wage of employed staff and workers (WAGE) – also have small bandwidths, with the influencing ranges covering 56 cities and 63 cities respectively. This significant spatial non-stationarity results from the differences in agglomeration levels of economic development across different regions.

The environmental indicators have larger bandwidths than the aforementioned three variables, among which the effect of green space area per capita (GREEN) covers 144 cities and the effect of sulfur dioxide emissions (EMI) affects 162 cities. The t statistics of TINDUS, FDI, EXP, and EMP are not significant, indicating that these variables have no major influences on innovation; thus, we shall not discuss the scale implications of their bandwidths. Some variables such as TINDUS, FDI, and EXP can be regarded as global variables – spatially stationary variables – having a bandwidth value of 287, which means that the influencing range covers all of the other cities.

Conclusions and Discussion

Drawing on the data from China's patent full-text database of 2016, the 1% national population sampling survey of 2015, and the *China City Statistical Yearbook 2016*, we have investigated the determinants of innovation at the city level and the spatial patterns of their effects through MGWR models, thus contributing to the growing literature on urban innovation in China from the perspective of spatially-varying effects. We have summarized the main discoveries in the subsequent paragraphs.

In this study, we have employed nationally-representative data at the city level to prove that human capital has a remarkable impact on the promotion of urban innovation. As a knowledge-intensive activity, innovation is highly dependent on human capital. Innovative individuals who have professional knowledge and skills are at the very foundation of enhancing the innovation capacity in a city. Meanwhile, various factors such as industrial structures (the proportion of secondary industry output value to GDP), research and development investments (the public finance expenditure on science and education), the environmental quality (the area of green space per capita and the volume of sulfur dioxide emissions), and the economic development level (the average wage of employed staff and workers) are also significant in the context of urban innovation: a finding which is consistent with the results of extant studies.

Furthermore, via MGWR models, we have revealed the spatial patterns of the effects of different variables on innovation. Regarding human capital (EDU) and the average wage of employed staff and workers (WAGE), their positive effects on innovation decrease from east to west, with high values being concentrated in principal urban agglomerations such as the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei urban agglomerations. For the proportion of secondary industry output value to GDP (SINDUS), the positive effects are most influential in the urban agglomerations of Pearl River Delta and Yangtze River Delta, while they are a lot weaker in northern China, western and northeastern regions. Concerning the sulfur dioxide emissions (EMI) and the green space area per capita (GREEN), the former negative impacts and the latter positive impacts both diminish from south to north, while the Circum-Bohai Sea Region also demonstrates the strong negative effects of sulfur dioxide emissions on innovation.

In addition, different bandwidths of different variables in the MGWR model indicate multi-scale effects. The spatial variations of the estimators of human capital and economic factors(SINDUS and WAGE) are larger than the other variables, and the effects of these factors on innovation vary greatly among prefecture-level cities. Their influencing ranges cover only a city cluster consisting of 47, 56, 63 cities respectively. The effects of human capital and economic factors on innovation are based more on agglomeration economies, with the influencing ranges confined to main urban agglomerations that have more developed scale economies. However, the spatial variations of the estimators of environmental indicators – namely, the sulfur dioxide emissions and the green space area per capita – are much smaller and the geographic location plays a far less significant role. The effects of environmental indicators on innovation do not vary dramatically over space, with vast influencing ranges being consistent with the natural environmental differentiation between the south and the north in China.

The spatially-varying effects of human capital on innovation can be explained from the perspectives of the Marshallian externalities, Jacobian externalities, and urban amenities. Firstly, Marshallian externalities can explain this phenomenon. According to the view of Marshall (1890), the agglomeration economy will generate externalities, such as the convenience of specialized input supply, the availability of a specialized workforce, and new ideas that are based on information exchange and face-to-face communication (Fujita & Thisse, 2002). Therefore, in the context of scale economy, it is more likely that human capital will cause knowledge spillover, thus greatly promoting innovation growth and economic development. Secondly, Jacobian externalities also contribute to this spatial variation, which emphasizes the agglomeration economic effects among industries complementary to each other within a city (Jacobs, 1969). A city with diverse industries often possesses stronger innovation capacity, since human capitals from different industries can exchange skill and knowledge with each other at low costs, and then generate knowledge spillover and technological innovations (Fujita, 2007). Thirdly, urban amenities also affect this spatially-varying relationship between human capital and innovation. Some scholars focus on the effects of urban amenities on talent agglomeration and innovation (Clark et al., 2002; Florida, 2003; Florida et al., 2008; Glaeser et al., 2001), including inclusiveness, consumption diversity, transportation infrastructure, public services, etc. In China, due to the specific *hukou* system and the government-dominated urban construction administration system, the developed urban agglomerations often have better amenities, which provide more comfortable space for face-to-face communication of talents and then inspire innovation.

What's more, this study has contributed to the growing literature on the determinants of regional innovation in the following three ways. Firstly, this study incorporates the space factor into the conventional innovation models, which neglected the spatial dimension and the importance of regions and cities in the innovation process (Glaeser, 2011; Shearmur, 2012; Tukiainen et al., 2015). Our study adds economic and environmental indicators based on the inputs of physical capital and human capital in the traditional production function of innovation (KPF) and introduces the spatial heterogeneity into the model to capture the spatially-varying effects of variables through MGWR, making the conventional innovation model closer to reality. Secondly, this study considers not only the spatial heterogeneity of influencing effects on innovation but also the different influencing ranges of different determinants with the MGWR model. Extant studies on the spatial effects of human capital on innovation mostly focus on the spatial dependence and spatial spillover effects (Chi & Qian, 2010; Marrocu et al., 2013; Ning et al., 2016; Qian et al., 2010; Zhang & Shi, 2018). Kang and Dall'erba (2016)' study are similar to ours in that it investigates the spatial heterogeneity in the marginal effects of the knowledge input variables at the county level in the United States, while we have employed China's city-level data to examine the spatially-varying relationship between innovation and its influencing factors and to explore the multi-scale effects of different variables. Thirdly, this study extends the existing scholarship on China's regional innovation from the traditional provincial level to the more reasonable city level, since cities act as collectors of human capital and incubators of innovation. When compared with provincial-level studies, research at the city level can reveal urban heterogeneity and intercity externalities within provinces. In comparison with city-level studies, our study focuses on the spatially-varying relationship between innovation and its determinants while other studies foreground the spatial dependence and spatial spillover effects (Ning et al., 2016; Rodríguez-Pose & Zhang, 2019). To summarize, the novelty of our study is that it is the first to identify the spatial variations between urban innovation and its influencing factors in China, with different influencing ranges based on the MGWR model. This study can also be regarded as a starting point for future explorations into the location-specific factors to which innovation is closely related.

Last but not least, the findings of this study have specific policy implications. Firstly, this article verifies the vital role of human capital in influencing urban innovation. Since it has currently entered the critical period of economic development transition to achieve the goal of reaching the forefront of innovative countries by 2035, China must increase its levels of investment in human capital, and improve the advancement mechanisms of innovation by making the most of human capital. Specifically, governments should increase their levels of investment in education and improve the quality of education, especially in terms of prioritizing the development of higher education to guide talented individuals to the front line of scientific and technological innovation. Moreover, in doing so, they would improve their talent evaluation mechanisms by increasing the proportion of technological innovation that is being evaluated, thus improving the quality of human capital and facilitating the output of urban innovation. In addition, economic elements, environmental factors, and public services are also important determinants in promoting urban innovation. Hence, related policies of economic development, environmental protection, and the provision of public services ought to be considered carefully.

More importantly, by using the MGWR model, we have shown that the effects of different variables on urban innovation vary spatially, with different spatial patterns and different influencing ranges. The results of the spatially-varying effects can offer support to local governments to formulate place-tailored segmentation innovation strategies. For instance, since the influencing effects of human capital and economic factors on innovation are more significant in eastern coastal regions – especially in the urban agglomerations of Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei – the cities in these regions should attach more importance to investing in human capital and economic development, thus generating stronger agglomeration effects. Whereas the cities in the comparatively less-developed central and western regions are supposed to lay a solid foundation by developing local infrastructure and institutional environments to make the essential inputs of innovation more effective. Similarly, the cities in the southern regions of China ought to place more emphasis on the environmental quality to accelerate the pace of innovation. In general, agglomeration economic effects that have been caused by rapid urbanization can significantly improve human capital, thus enhancing the innovation capacity of a city. To enlarge the effective role of the agglomeration economy, the development of China's new-type urbanization and the improvement of urban infrastructure should be given more attention. In the regions which have a relatively strong agglomeration economy, human capital has intensified the effects on innovation. Consequently, for agglomeration economic zones – such as main urban agglomerations – local governments are supposed to follow the rules of market development and actively guide the driving effects of human capital on innovation, such as providing more platforms and facilities for talent exchange and formulating policies to control the effects of negative crowding and vicious competition. For non-agglomeration economic zones, local governments are obliged to promote talent aggregation by guiding industrial clustering, building social networks, improving public services and reinforcing environmental governance, to facilitate regional innovation. Meanwhile, local governments need to realize that the effects of economic development, environmental quality, and public services on innovation also present spatial variation characteristics and adjust their policies of regional economic development to local conditions accordingly. Finally, the central government should pay more attention to non-agglomeration economic zones by providing policy preferences for the cultivation of regional talents, presenting policies of balanced regional development to avoid the widening gap of regional innovation and regional economic development.

Despite its significant methodological and practical implications, this study inevitably has limitations. As the innovation of a city is a complex phenomenon that is affected by multiple factors in various ways, this study – based on the cross-sectional data due to the limited availability of data(lacking time series data of human capital) and the constraints of the MGWR model – cannot deliver some of the advantages of panel data analysis such as temporal changes of variables. Moreover, we have employed the MGWR model to reveal the influencing range on the innovation of each variable. Nevertheless, we cannot discuss the underlying mechanism of this multi-scale effect in-depth, limited by the extant theories and the nature of an exploratory data analysis of the MGWR model.

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Declarations

Conflict of interest The authors claim that they have no conflict of interest.

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