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An analysis of the paradox in R&D. Insight from a new spatial heterogeneity model

Abstract
The relationship between research and development (R&D) and economic growth is a hot topic. Most research indicates that R&D leads to innovation, which is conducive to economic growth. However, some scholars hold a different opinion, alleging that high R&D investment will not bring high economic growth. This scenario is also known as the Swedish paradox. We develop a new spatial heterogeneity model in the form of a mixed geographically weighted panel regression with spatial Durbin model (MGWPR-SDM). Using this model, we add to the debate over the possible existence of a Swedish paradox in China. The results show that the impact of aggregate R&D expenditure on economic growth follows an inverted U-shaped curve. The Swedish paradox appears after a threshold is reached, mainly due to business enterprise R&D expenditure rather than government R&D investment. However, from the perspective of R&D input per unit GDP, the impact of R&D intensity on economic growth is U-shaped, and the Swedish paradox occurs before the threshold is reached. Finally, the effect of government R&D expenditure and business enterprise R&D expenditure on economic growth has significant spatial heterogeneity.

Keywords: R&D; Swedish paradox; economic growth; spatial heterogeneity; MGWPR-SDM

1. Introduction

Research and development (R&D) is a determinant of long-run productivity and welfare (Jones and Williams, 2000). The experience of developed countries has shown that leading countries in innovation and R&D have higher economic growth than other nations (Samimi and Alerasoul, 2009). However, Bilbao-Osorio and Rodriguez-Pose (2004) and Fragkandreas (2013) has provided evidence of the *Swedish paradox*. This paradox refers to the fact that Sweden is inefficient in transforming its high R&D expenditure into productivity and growth (Andersson et al., 2002; Edquist, 2002; OECD, 2005). Many scholars have researched this topic. Most research indicates that R&D investment can effectively promote economic growth. However, some scholars argue that R&D investment has not played such a role, claiming that the Swedish paradox is in fact a real phenomenon (Ejermo et al., 2011; Shang'ao et al., 2011; Ye et al., 2018).

There are three possible reasons for this dispute. First, regional spatial heterogeneity is likely to lead to such disputes. Despite the different resource endowments, socioeconomic conditions (e.g., absorptive capacity, tax, and innovation policy) and cultural background of different countries, few scholars have studied this issue from the perspective of geographical spatial heterogeneity (Haq, 2018). Second, the impact of R&D on economic growth is not simply positive or negative. Instead, there may be an inverted U-shaped relationship between the two (Kim, 2020). Third, different types of R&D investment, such as government R&D and private enterprise R&D, have different levels of efficiency, which leads to different conclusions (Jacobson et al., 2013; Kacprzyk & Świeczewska, 2019; Xiong et al., 2020). Most of the related research uses aggregate data for the regression analysis, offering conclusions based on the mean value. However, few studies have taken these three aspects into account at the same time.

In this paper, we fill the gap in the literature by developing a new spatial heterogeneity model in the form of a mixed geographically weighted panel regression with spatial Durbin model (MGWPR-SDM). We thus add to the debate over whether a Swedish paradox exists in China. We divide aggregate R&D investment into government R&D investment and enterprise R&D expenditure. In addition, we include the square term of R&D investment in the model. Thus, we comprehensively examine the impact of R&D input on regional economic growth by considering these three sides of R&D expenditure.

2. Theoretical framework

Much empirical research has been conducted to verify whether R&D expenditure can promote economic growth. However, scholars have never reached a consensus, and even the conclusions of studies of the same region are quite different.

Romer (1990), and Lichtenberg (1993) have reported that the relationship between investment in technology and R&D expenditure increases productivity and therefore growth (Bilbao-Osorio and Rodriguez-Pose, 2004). This finding is supported by many empirical findings. Hall (1996) showed that investment in R&D is positively correlated with productivity and profitability at the firm level. Zachariadis (2003) provided strong evidence that R&D investment and growth are positively related in the U.S. economy (Sveikauskas, 1986; Rabiei, 2011; Blanco et al., 2016). However, Comin (2004) did not find R&D to be responsible for nearly as much of actual growth in the U.S. after 1950 as Jones and Williams (2002) did. The contribution of R&D was found to be quite small—only 0.1 times the observed growth rate. Sadraoui and Zina (2009) examined the dynamic relationship between cooperation in R&D and economic growth using panel data from a sample of 23 countries between 1992 and 2004. The results suggest a positive and significant relationship between R&D cooperation and economic growth. Dam and Yildiz (2016) studied panel data on the BRICS-TM countries (Brazil, Russia, India, China, South Africa, Turkey, and Mexico) for 2000 to 2012, showing that the impact of R&D and innovation are positively related to economic growth. Türedi (2016) proposed two-way positive causality between R&D expenditure and economic growth for the 23 OECD member countries between 1996 and 2011, consistent with the conclusions of Badri et al. (2019).

Moutinho (2017) reported that government R&D investment could be effective in enhancing GDP growth, even in technologically underdeveloped regions, and could also enhance mass-market employment growth, but only if coupled with effective corporate R&D. Edquist and Henrekson (2017) reported that both ICT and R&D capital are positively associated with value added in the Swedish non-farm business sector. Szarowská (2018) found that dynamic panel analysis conclusively confirms a positive and significant impact of R&D expenditure on economic growth in Central and Eastern European (CEE) countries. Sokolov-Mladenović et al. (2016) reached the same conclusion. Kaneva and Untura (2019) found that both R&D and TI had a significant and positive effect on GDP per capita growth from 2005 to 2013 in Russia.

Some conflicting findings suggest that R&D may not promote economic growth. Ulku (2004) analyzed patent and R&D data for 20 OECD and 10 non-OECD countries, both developed and developing, for the period 1981 to 1997. The effect of R&D stock on innovation was observed to be significant only in OECD countries with large markets. Ejermo et al. (2011) showed that "the Sweden Paradox occurs only in fast-growing manufacturing and service sectors" and not in slow-growing sectors (cf. Edquist and Mckelvey, 1998), which is exactly the opposite of the findings of Wang et al. (2013). The analysis by Bayarcelik et al. (2012) showed that R&D expenditure in Turkey has a positive impact on economic growth. In contrast, Tuna et al. (2015) found that there is no co-integration relationship or causal relationship between R&D expenditure and economic growth, based on data for Turkey from 1990 to 2013. Kacprzyk and Świeczewska (2019) found a significant positive link between business R&D stock and economic growth in EU countries that are relatively close to the frontier. Still, no significant relationship was found to exist between government R&D stock and economic growth. Similarly, the explanation that government-funded R&D activities are not efficient enough is also popular on the paradox (Granberg and Jacobsson, 2006; Hellström and Jacob, 2005; Henrekson and Rosenberg, 2001; Jacobsson et al., 2013; Jacobssson and Rickne, 2004). Samimi and Alerasoul (2009) even concluded that the low R&D expenditure by 30 developing countries had no significant effect on economic growth between 2000 and 2006. Kim (2020) reported an inverted U-shaped relationship between the concentration of R&D investment and economic growth in 14 countries over the period 1996 to 2013. Some level of concentration may be good for growth. However, beyond a certain point, concentration hurts growth (Wu et al., 2020).

The debate over whether there is a Swedish paradox in China continues. Liu and Cheng (2011) reported that domestic R&D, domestic R&D in other industries, and foreign R&D capital have significant positive effects on productivity. Research by Ma (2014) showed that the role of R&D human resources investment in economic growth is relatively prominent in the long run, while financial resources investment has a more significant short-term impact on economic growth. Similarly, Lu and Jin (2011) reported that the output elasticity of R&D personnel input is greater than that of R&D funding input. Wang and Wu (2015) observed that unlike the strong correlation with enterprise R&D, the correlation between government R&D expenditure and economic growth is nearly zero. Liu and Wang (2017) found that nationwide R&D has become the most important factor behind the capital in the input factors that drive economic growth, and direct R&D and indirect R&D contribute equally to economic growth. From the perspective of different regions, the eastern region of direct R&D and indirect R&D has the largest driving effect, and it has a gradually declining trend in the east, middle, and west. The simulation results of Zheng et al. (2018) indicate that R&D investment has a significant impact on the macro economy. Positive effects promote the growth of total output value, reduce prices, boost domestic demand and exports, and improve residents' welfare. Public R&D investment has a more significant impact on economic growth than private R&D investment.

However, Gao (2017) found that, since 2001, with the increase in intensity of technological innovation input, China's total factor productivity (TFP) growth rate and its contribution to economic growth have gradually declined. Taking 2008 as the watershed, a *scissors difference* between the two has begun to appear, expanding year on year. This phenomenon is known as the mystery of innovation in China's economic development process or the solo paradox of China's R&D investment (Li et al., 2017). It is an important characteristic of China's economic system in the context of the new normal (Shujun, 2019). Wu (2008) argued that in industries with a high proportion of state-owned property rights, R&D does not promote productivity. Gu and Ren (2015) showed that the level of R&D does not play a significant role in driving China's economic growth. Ye and Liu (2018) also noted the dilemma of China's scientific and technological innovation, reporting that scientific research has not improved TFP in the short-term direct impact. Technology development has a significant inhibitory effect on improving total factor productivity. Fan et al. (2008) analyzed China's R&D input and GDP data from 1987 to 2005 and reached a similar conclusion: In the long run, there is a stable and balanced relationship between R&D input and China's economic growth, but the change in R&D input is not a Granger cause of economic growth. Research by Li et al. (2011) showed that the rapid development of R&D leads to rapid technological progress and the slow accumulation of human capital. Human capital is currently insufficient to fully understand and flexibly use new technologies. This situation has produced an erosion effect, which has further reduced the efficiency of human capital accumulation, exacerbated the gap between technological progress and human capital accumulation, worsened the allocation of social resources, and reduced the economic equilibrium growth rate. Zhang et al. (2016) argued that under the influence of technological gaps, China's R&D has not fully exerted its driving effect on technological progress. Ren (2017) also confirmed this point, noting numerous cases of the Swedish paradox in regional development in China. That is, innovation investment may not necessarily translate into economic growth. Therefore, this paper addresses one question: Does a Swedish paradox exist in China, or does China's R&D expenditure promote economic growth? The paper thus advances the debate surrounding this issue.

Most studies suggest that R&D positively affects economic growth. China, a developing country, has a vast land area similar to that of Europe. However, Europe comprises 47 countries with major differences in their socioeconomic environments. Analogously, China has 34 provincial administrative regions, and the socioeconomic environment in each province, city, and autonomous region also has significant spatial heterogeneity. The impact of R&D investment on economic growth varies in different regions. Therefore, when considering the impact of R&D investment on economic growth, the spatial variable coefficient model must be used to consider regional heterogeneity. However, most of the aforementioned empirical studies fail to consider spatial heterogeneity. Instead, they produce estimates of the average across all sample areas. Studies that consider spatial heterogeneity and spatial correlation in sample areas are rare. We develop a new model to cover this gap. This new model also corresponds to the innovation of this paper. Most of the abovementioned studies consider the direct impact of aggregate R&D investment cost on economic growth. The weakness of this approach is that the conclusions are too general.

This paper focuses on the following issues: Is the impact of R&D investment on China's economic growth positive or negative? What is the stage of negative impact or positive impact? Is there spatial heterogeneity in this impact? What determines this impact?

The remainder of the paper is organized as follows. Section 3 presents the model and estimation method, including a description of the data and variable selection. Section 4 presents the empirical analysis, including testing and analysis of the empirical results. The conclusions and a discussion of the findings are provided in Section 5.

3. Model and estimation method

This study uses provincial panel data covering 31 provinces, municipalities, and autonomous regions in China from 2013 to 2017. The core variables are R&D expenditure (RD) and its square term (RD^2). The explanatory variable is GDP, representing the level of economic development. The control variables are the spatial lag of the explanatory variable (WY), the level of capital accumulation (K), the amount of labor (L), the full-time equivalent of R&D personnel (RL), and the spatial lag of the explanatory variable. All data were sourced from the China Statistical Yearbook on Science and Technology and the National Bureau of Statistics website.

Fixed effects MGWPR-SDM model construction

The classic Cobb-Douglass production function is:

$$Y_{it} = TFP_{it} K_{it}^{\alpha} L_{it}^{\beta} \qquad (1)$$

where Y represents the output level, A represents technological progress, α and β are the output elasticity values corresponding to the capital K and labor L, respectively, and i and t represent the region and time, respectively. Taking the logarithm of both sides and adding the residual term gives the following model:

$$\ln Y_{it} = \ln TFP_{it} + \alpha \ln K_{it} + \beta \ln L_{it} \qquad (2)$$

Technological progress is the result of technological innovation due to R&D. Thus, A represents technological progress, which can be expressed as:

$$TFP_{it} = A_{it} RD_{it}^{\gamma} RL_{it}^{\lambda} \qquad (3)$$

where A is the unexplained technical change, RD is R&D investment, and RL is the full-time equivalent of R&D personnel. Thus,

$$\ln Y_{it} = \ln A_{it} + \gamma \ln RD_{it} + \lambda \ln RL_{it} + \alpha \ln K_{it} + \beta \ln L_{it} + \varepsilon_{it} \qquad (4)$$

Some scholars have observed that the influence of the coefficient of R&D on economic growth is positive, and some have found this influence to be negative, probably because of the U-shaped relationship between the two (Mao et al., 2013; Kim, 2020). Therefore, we add the square term of RE to the model given in Eq. (4) to give the following equation:

$$\ln Y_{it} = \ln A_{it} + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln RD_{it} + \lambda \ln RL_{it} + \psi RE^2{}_{it} + \varepsilon_{it} \qquad (5)$$

If all parameters, α β γ λ ψ , change with the geographical location, then the model in Eq. (5) changes as follows:

$$\ln Y_{it} = \ln A_{it} + \alpha_{(i)} \ln K_{it} + \beta_{(i)} \ln L_{it} + \gamma_{(i)} \ln RD_{it} + \lambda_{(i)} \ln RL_{it} + \psi_{(i)} RD^2{}_{it} + \varepsilon_{it} \qquad (6)$$

where i is location. If there is spatial autocorrelation of the dependent variable Y, we should add the spatial lag term of the dependent variable (WY) to the model. Thus, the model can be rewritten as:

$$\ln Y_{it} = \rho \ln WY_{it} + \ln A_{it} + \alpha_{(i)} \ln K_{it} + \beta_{(i)} \ln L_{it} + \gamma_{(i)} \ln RD_{it} + \lambda_{(i)} \ln RL_{it} + \psi_{(i)} RD^2{}_{it} + \varepsilon_{it}$$
(7)

where, $W = I_T \otimes W_N$, W is the spatial distance matrix, I_T is the *T*-dimension identity matrix, and W_N is the row normalized spatial weight matrix with all diagonals in the *N*×*N* dimension. The selection methods include Rook adjacent, Queen adjacent, and KNN. In this paper, the classic (0,1)-matrix of Queen adjacent space is used. If two regions are neighbors, the value is 1; otherwise, it is 0.

Some of the explanatory variables may also have spatial correlation, which should be considered in the model. Hence, Eq. (7) can be rewritten as:

$$\begin{aligned}\ln Y_{it} = \rho \ln WY_{it} + \ln A_{it} + \alpha_{(i)} \ln K_{it} + \beta_{(i)} \ln L_{it} + \gamma_{(i)} \ln RD_{it} + \lambda_{(i)} \ln RL_{it} \\ + \psi_{(i)} RD^2{}_{it} + \xi_{(i)j} \sum_{j=1}^{l} WX_{j,it} + \varepsilon_{it}\end{aligned} \tag{8}$$

We can rewrite Eq. (8) in a more compact matrix form as:

$$Y = \mu \otimes \iota_T + \rho WY + K\alpha + L\beta + RD\gamma + RL\lambda + RD^2\psi + WX\theta + \varepsilon \tag{9}$$

where *Y* is a vector with dimension *NT×1* and μ is the individual effect term with dimension *N*1* (i.e., technical progress *lnA* in Eq. (8)). The two can be regarded as the same thing, namely the intercept term. Because the data in this paper are short panel data, technological progress can reasonably be expected to vary from region to region but remain constant in the short term. The term ι_T is a T×1 dimension vector. *K*, *L*, *RE*, *RL*, and the error term are all *NT×1* vectors. The term *WX* is an $NT \times l$ matrix, which contains the spatial lag term of the l explanatory variables. Actually, all coefficients corresponding to these explanatory variables may be varying coefficients (that change with spatial location) or fixed coefficients (that do not change with spatial location). Therefore, Eq. (8) can be rewritten as:

$$Y = \mu \otimes \iota_T + \rho WY + X_c \lambda_c + X_v \lambda_{v(u_i, v_i)} + \varepsilon \tag{10}$$

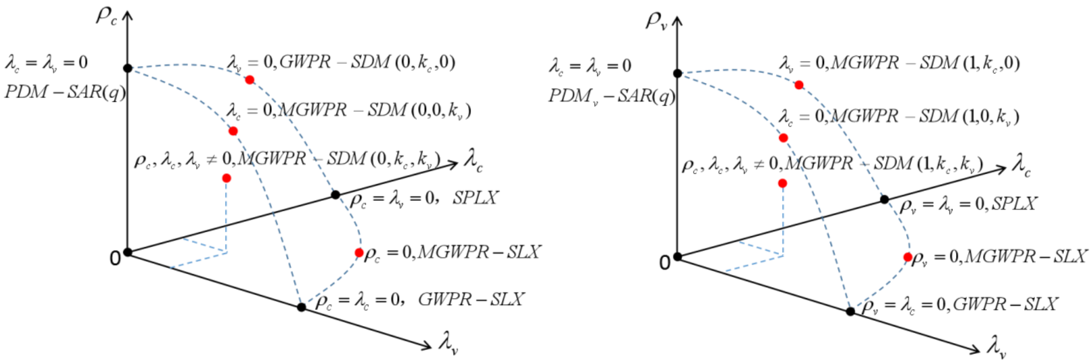
Eq. (10) above is a benchmark model, used to derive all the following formulas. The term X_c represents the fixed coefficient variable, and λ_c is the corresponding coefficient matrix. The term X_v is the variable coefficient variable, the corresponding coefficient matrix is $\lambda_{v(u_i, v_i)}$, and (u_i, v_i) is the latitude and longitude of spatial location *i*. The term ρ is the spatial lag coefficient of the dependent variable. It is used to describe spatial autocorrelation. It can be a varying coefficient or a fixed coefficient. Due to its special characteristics, it will be discussed separately later.

If all the coefficients of the explanatory variables in Eq. (10) are varying in space, then we can use a geographically weighted panel regression (GWPR) model (Yu, 2010), which is based on a geographically weighted regression (GWR) model (Brunsdon et al., 1996; Fotheringham et al., 2003). However, this model does not consider the endogenous spatial lag term of the dependent variable (*WY*). If only some of the coefficients change with spatial location, we should use the mixed geographically weighted panel regression (MGWPR) model, which is a kind of semi-parametric model. However, according to the literature, there are no similar models for panel data, except the MGWR-SAR and SAR-GWR models proposed by Geniaux and Martinetti (2018) and Jaya et al. (2018) for cross-sectional data. None of these models can be used to solve Eq. (10). Therefore, based on the above models, we propose a more generalized fixed effects MGWPR-SDM model applicable to spatial panel data. The proposal of this model is one of the innovations of this paper.

The proposed model (MGWPR-SDM) is a more generalized model because Eq. (10) can be reduced to three spatial panel model clusters. Let $\theta = 0$ and $\rho \neq 0$, then Eq. (10) is the MGWPR-SAR model cluster. Let $\rho = 0$ and $\theta \neq 0$, then Eq. (10) is the MGWPR-SLX model cluster. Let $\rho \neq 0$, $\theta \neq 0$, and $\theta + \beta\rho = 0$, then Eq. (10) is the MGWPR-SEM model cluster. Each model cluster can be subdivided into several sub-models. For example, the MGWPR-SDM model cluster can be changed into the eleven models shown in Eq. (11), eight of which are new.

$$\begin{cases}
Y = \mu \otimes \iota_T + \rho_{(u_i,v_i)} WY + X_c \lambda_c + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{MGWPR-SDM}(1, k_c, k_v)) \\
Y = \mu \otimes \iota_T + \rho WY + X_c \lambda_c + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{MGWPR-SDM}(0, k_c, k_v)) \\
Y = \mu \otimes \iota_T + \rho WY + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{MGWPR-SDM}(0,0, k_v)) \\
Y = \mu \otimes \iota_T + \rho_{(u_i,v_i)} WY + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{MGWPR-SDM}(1,0, k_v)) \\
Y = \mu \otimes \iota_T + \rho_{(u_i,v_i)} WY + X_c \lambda_c + \varepsilon & (\text{MGWPR-SDM}(1, k_c, 0)) \\
Y = \mu \otimes \iota_T + \rho WY + X_c \lambda_c + \varepsilon & (\text{GWPR-SDM}(0, k_c, 0)) \\
Y = \mu \otimes \iota_T + X_c \lambda_c + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{MGWPR-SLX}) \\
Y = \mu \otimes \iota_T + \quad + X_v \lambda_{v(u_i,v_i)} + \varepsilon & (\text{GWPR-SLX}) \\
Y = \mu \otimes \iota_T + X_c \lambda_c + \varepsilon & (\text{SPLX}) \\
Y = \mu \otimes \iota_T + \rho_{(u_i,v_i)} WY + \quad + \varepsilon & (\text{PDM}_v\text{-SAR(q)}) \\
Y = \mu \otimes \iota_T + \rho WY + \quad + \varepsilon & (\text{PDM-SAR(q)})
\end{cases}$$

(11)



(a) ρ is a fixed coefficient (b) ρ is a variable coefficient

Figure 1: The nested diagrams of the MGWPR-SDM model

①When ρ is a fixed coefficient and ρ, λ_c, and $\lambda_v \neq 0$, then Eq. (10) becomes the model $MGWPR-SDM(0,k_c,k_v)$, where X_c or X_v contains the spatial lag term of some explanatory variables.

②When ρ is a fixed coefficient and $\lambda_c = 0$, then Eq. (10) becomes the model $MGWPR-SDM(0,0,k_v)$, where X_v contains the spatial lag term of some explanatory variables.

③When ρ is the fixed coefficient and $\lambda_v = 0$, then Eq. (10) becomes the model $GWPR-SDM(0,k_c,0)$, which is the ordinary spatial Durbin panel model (SPDM), where X_c contains the spatial lag term of some explanatory variables.

④When ρ is a variable coefficient and ρ, λ_c, and $\lambda_v \neq 0$, then Eq. (10) becomes the model $MGWPR-SDM(1,k_c,k_v)$, where X_c or X_v contains the spatial lag term of some explanatory variables.

⑤When ρ is a variable coefficient, $\rho \neq 0$, and $\lambda_c = 0$, then Eq. (10) becomes the model $MGWPR-SDM(1,0,k_v)$, where X_v contains the spatial lag term of some explanatory variables.

⑥When ρ is a variable coefficient and only $\lambda_v = 0$, then Eq. (10) becomes the model $MGWPR-SDM(1,k_c,0)$, where X_c contains the spatial lag term of some explanatory variables.

⑦If $\rho = 0$ and λ_c and $\lambda_v \neq 0$, then Eq. (10) changes into the MGWPR-SLX model, where X_c or X_v contains the spatial lag term of some explanatory variables.

⑧If $\rho = \lambda_c = 0$, then Eq. (10) changes into the GWPR-SLX model, where X_v contains the spatial lag term of some explanatory variables.

⑨If $\rho = \lambda_v = 0$, then Eq. (10) changes into a spatial panel with spatial lags of explanatory variables (SPLX) model, where X_c contains the spatial lag term of some explanatory variables.

⑩When ρ is a fixed coefficient, $\rho \neq 0$, and $\lambda_c = \lambda_v = 0$, then Eq. (10) changes into the pure spatial autoregression panel data model PDM-SAR(q).

11 When ρ is a variable coefficient, $\rho \neq 0$, and $\lambda_c = \lambda_v = 0$, then Eq. (10) changes into the pure spatial autoregression panel data model PDM_v-SAR(q), and the coefficient varies with geographical location.

In practice, the selection of the most suitable model requires a series of tests, which are mentioned in Part 3. Because the individual effect μ is related to a certain explanatory variable in the panel model, ordinary least squares (OLS) cannot be used to obtain a consistent estimate. Therefore, based on the model estimation by Qurani (2014) and Meutuah et al. (2017), we use the first-order difference method to eliminate the individual effect term and give the estimation process using the fixed effects MGWPR-SDM model.

First, after it has been averaged by time, Eq. (10) can be rewritten as:

$$\bar{Y} = \mu \otimes \iota_T + \rho W\bar{Y} + \bar{X}_c \lambda_c + \bar{X}_v \lambda_{v(u_i,v_i)} + \bar{\varepsilon} \qquad (12)$$

By subtracting Eq. (12) from Eq. (10), we get:

$$Y - \bar{Y} = (\mu \otimes \iota_T - \mu_i \otimes \iota_T) + (\rho WY - \rho W\bar{Y}) + (X - \bar{X}_c)\lambda_c + (X_v - \bar{X}_v)\lambda_{v(u_i,v_i)} + \varepsilon - \bar{\varepsilon}$$

This equation can be further abbreviated to:

$$\breve{Y} = \rho W\breve{Y} + \breve{X}_c \lambda_c + \breve{X}_v \lambda_{v(u_i,v_i)} + \breve{\varepsilon} \qquad (13)$$

where $\breve{Y} = Y - \bar{Y}$, $\breve{X}_c = X_c - \bar{X}_c$, $\breve{X}_v = X_v - \bar{X}_v$, and $\breve{\varepsilon} = \varepsilon - \bar{\varepsilon}$. The following model estimates are based on this equation.

Fixed effects MGWPR-SDM model estimation

A key assumption of the traditional GWR model is that there is spatial heterogeneity but not spatial autocorrelation. This assumption is also the model's weakness (Geniaux & Martinetti, 2018). The MGWPR-SDM model proposed in this paper for panel data not only simultaneously takes into account spatial heterogeneity and spatial autocorrelation but also offers richer information, stronger economic interpretations, and broader applicability than the GWR cluster cross-sectional model. For spatial heterogeneity, it can be characterized by the varying coefficient of the explanatory variable in the model. In contrast, spatial autocorrelation can be characterized by the coefficient of the spatial lag term of the dependent variable. In practical applications, it can be divided into two cases: ρ is the varying coefficient and ρ is the constant coefficient, corresponding to MGWPR-SDM(1,k_c,k_v) and MGWPR-SDM(0,k_c,k_v), respectively. Therefore, these two cases must be discussed separately. We give the estimation processes for these two types of models only because other types of models are simply special cases of these two. The estimation method of the model mainly follows the two-step method proposed by Fotheringham et al. (2003). The advantage of this method is that it is less computationally intensive than the method recommended by Brunsdon et al. (1999) and has high accuracy (Fotheringham et al., 2003). The derivation of the fixed effects MGWPR-SDM model is shown in Appendix A. Here, we give the estimation results first.

(1) when $\rho \neq 0$ and ρ is the varying coefficient, the estimation result of the MGWPR-SDM(1,k_c,k_v) model is as follows:

$$\begin{cases} \hat{\lambda}_c = [X_c'(I-S)'(I-S)X_c]^{-1} X_c'(I-S)'(I-S)Y \\ \hat{\delta}_{(u_i,v_i)} = (\hat{Z}'G\hat{Z})^{-1}\hat{Z}'G(Y - X_c\hat{\lambda}_c) \end{cases} \qquad (14)$$

(2) when ρ ≠ 0 and ρ is a constant coefficient, the estimation result of the MGWPR-SDM(0,k_c,k_v) model is as follows:

$$\begin{cases} \widehat{\delta} = [Z'(I-S)'P_H(I-S)Z]^{-1}Z'(I-S)'P_H(I-S)Y \\ \widehat{\lambda}_{v(u_i,v_i)} = (\widehat{X}_v'G\widehat{X}_v)^{-1}\widehat{X}_v'G(Y-Z\widehat{\delta}) \end{cases} \tag{15}$$

The first column of the coefficient matrix is the spatial autocorrelation coefficient ρ, and the rest is λ_c. The above estimation results indicate that the results of the two cases differ depending on whether the lag coefficient of the dependent variable space is varying.

4.Empirical analysis

Model identification and testing

In this section, three kinds of tests are needed to determine to which model in Eq. (11) the data apply. We must first check whether a spatial model is needed, usually by employing Moran's I test. Second, we must test whether the panel model is a fixed effects or random effects model. The third test is to decide whether the coefficients of each explanatory variable are varying with spatial location.

（1）Model diagnostic 1: Moran's I test

$$I = \frac{1}{s^2}\frac{\sum_i \sum_j (y_i - \bar{y})(y_j - \bar{y})}{\sum_j w_{ij}}$$

Here, $\bar{y}$ is the mean of y, s^2 is its variance, and w_{ij} is the weight of the spatial distance from location *i* to location *j*. The null hypothesis (H_0) is that there is no spatial correlation of data and that the data follow a spatially random distribution. The alternative hypothesis (H_1) is that the data have spatial autocorrelation, in which case the spatial model method would be needed to process the data.

Table 1: Moran's I value for all variables

	GDP	K	L	rl	TotalRD	GovRD	EnterRD	Insten
2013	0.154	0.132	0.123	0.153	0.187	-0.011	0.206	0.27
	(0.051)	(0.08)	(0.084)	(0.048)	(0.028)	(0.388)	(0.017)	(0.002)
2014	0.154	0.119	0.129	0.172	0.196	-0.012	0.191	0.287
	(0.051)	(0.097)	(0.077)	(0.034)	(0.024)	(0.394)	(0.022)	(0.001)
2015	0.160	0.126	0.133	0.195	0.200	0.009	0.195	0.299
	(0.045)	(0.086)	(0.073)	(0.021)	(0.021)	(0.302)	(0.02)	(0.001)
2016	0.174	0.138	0.123	0.200	0.183	-0.011	0.210	0.292
	(0.035)	(0.072)	(0.084)	(0.019)	(0.03)	(0.396)	(0.015)	(0.001)
2017	0.174	0.105	0.130	0.174	0.187	-0.007	0.223	0.263
	(0.034)	(0.118)	(0.073)	(0.032)	(0.027)	(0.386)	(0.011)	(0.003)

Note: "TotalRD" is the aggregate R&D expenditure; "GovRD" is the government R&D expenditure; "EnterRD" is the business enterprise R&D expenditure; "Insten" is R&D intensity. The numbers in parentheses are the *p* values.

According to Moran's I test (Table 1), all variables except K, L, and GovRD have spatial correlation. Therefore, spatial correlation must also be included in the model, and a spatial econometric model must be used.

（2）Model diagnostic 2: Spatial Hausman test

According to the relationship between explanatory variables, an individual effects panel model can be divided into a fixed effects model and a random effects model. In this paper, the spatial Hausman test proposed by Mutl and Pfaffermayr (2011) was used to determine which model was most appropriate.

$$\mathrm{H} = \mathrm{NT}\,(\hat{\theta}_{\mathrm{FGLS}} - \hat{\theta}_{\mathrm{W}})^{\mathrm{T}}(\hat{\Sigma}_{\mathrm{W}} - \hat{\Sigma}_{\mathrm{FGLS}})^{-1}(\hat{\theta}_{\mathrm{FGLS}} - \hat{\theta}_{\mathrm{W}})$$

Here, $\hat{\theta}_{\mathrm{FGLS}}$ and $\hat{\theta}_{\mathrm{W}}$ are the spatial GLS estimator and the estimator in the spatial group, respectively, and $\hat{\Sigma}_{\mathrm{FGLS}}$ and $\hat{\Sigma}_{\mathrm{W}}$ are the variance-covariance matrices corresponding to their respective coefficients. The term H is subject to the χ^2 distribution with K degrees of freedom, and K is the number of explanatory variables in the model. The null hypothesis (H_0) is that the estimation coefficient of fixed effects and the estimator of random effects are consistent and most effective. The alternative hypothesis (H_1) is that the fixed effects estimator is consistent and inconsistent. This process can be implemented through the command “sphtest” in the R language package *splm*.

Table 2 : Test for model specification (fixed or random)

Diagnostic	Statistic	Value
Hausman test	$Chi^2(7)$	59.24 (p = 0.00)

The Hausman test shows that $\chi^2 = 59.24$. The corresponding p value is 0.00, which is less than the significance level of 0.05. Therefore, the null hypothesis H_0 is rejected, and we must select a fixed effects panel model. Also, the data in this paper are for provinces and municipalities in China, and the samples are almost all maternal samples rather than random samples. Hence, the random effects model can be dismissed.

（3）Variable selection: Bootstrap test

Drawing on the method proposed by Mei (2016), we used a bootstrap method to test whether some explanatory variables in the GWR model have fixed coefficients. This test method is more robust than the F test proposed by Brunsdon et al. (1999) and Leung et al. (2000). Both of these F tests neglect the dependence between the molecular and denominator of the statistic. The basic idea is that first, a GWR model is constructed. The optimal bandwidth *h* is calculated according to *minAICc*, and the sum of squares of errors, *RSSg*, is calculated. Second, the same bandwidth *h* is used to construct the MGWR model in GWR and calculate the sum of squares of residuals (RSSm). Finally, a *T* statistic is constructed as follows:

$$T = \frac{RSSm(h) - RSSg(h)}{RSSg(h)}$$

The null hypothesis (H_0) is that the model is the MGWR model. That is, the explanatory variable has a fixed coefficient. The alternative hypothesis (H_1) is that the model is the GWR model. That is, all explanatory variables follow spatial varying coefficient models. If the null hypothesis is not rejected, then the value of *RSSg* and *RSSm* should be close. Otherwise, the difference between the two is large. Bootstrap sampling was conducted *n* times based on residuals, and one t^* is calculated for each sample. The evaluation criterion is as follows:

$$P = P_{H_0}(T > t^*)$$

If P is less than the given significance level, the null hypothesis (H_0) is rejected, and the GWR model is selected. Otherwise, the MGWR model is selected. All explanatory variables are tested one by one to select which variables are fixed coefficients or varying coefficients. If all coefficient tests of explanatory variables are non-significant, the OLS regression model is selected.

Table 3: The *p* value of the bootstrap test

Items ~~Variables~~	Intercept	WY	K	L	rl	wrl	Expend	Splag	Square
Total RD	0.052	0.072	0.00	0.021	0.062	0.096	0.122	0.12	0.326
Gov RD	0.012	0.006	0.00	0.016	0.00	0.012	0.006	—	0.001
Enter RD	0.492	0.219	0.00	0.04	0.231	0.071	0.00	0.264	0.145
Intensity	0.033	0.027	0.00	0.047	0.00	0.031	0.008	0.061	0.009

Note：“Expend” is the corresponding R&D expenditure; “SPlag” is the spatial lag term of “Expend”; “Square” is the square term of “Expend”; “—” means that the variable does not exist because it failed to pass Moran’s I test.

For aggregate R&D expenditure (RD), only the bootstrap test *p* value of K and L is less than 0.05. This result implies that K and L are variable coefficient variables and that the others are fixed coefficient variables, including the spatial lag term WY of the explained variables (Table 3). Therefore, the MGWPR-SDM (0, k_c, k_v) model should be used. For government R&D investment (GovRD), the *p* value of the bootstrap test of all variables is less than 0.05. Thus, all variables are variable coefficient variables, including the spatial lag term WY of the interpreted variables. Hence, the MGWPR-SDM (1,0, k_v) model should be used. For business enterprise R&D expenditure (Enter RD), only the bootstrap test *p* values of K, L, and Expend are less than 0.05. Hence, K, L, and Expend are variable coefficient variables, and the others are fixed coefficient variables, including the spatial lag term WY of the interpreted variables. Therefore, the MGWPR-SDM (0, k_c, k_v) model should be used. Like Gov RD, R&D intensity should use the MGWPR-SDM(1,0,k_v) model too.

Analysis of empirical results

(1) Aggregate R&D expenditure

Table 4 shows that the aggregate R&D expenditure (TotalRD) has a positive effect on economic growth and that the aggregate R&D expenditure in the immediate area also has a positive impact on the region. Also, the results of the variable coefficients (Table 5) show that the elasticity of K to economic growth is greater than L in each quantile. The negative square coefficient (Table 4) suggests that there may be an inverted U-shaped relationship between aggregate R&D expenditure and economic growth. To analyze what causes the inverted U-shaped relationship, we further analyzed the impact of government R&D expenditure and business enterprise R&D expenditure on China's economic growth.

Table 4: Fixed coefficient estimate of aggregate R&D expenditure

Variable	Coefficient	*t* value	*p* value
WY	0.1444	14278.47	0.00
RL	-0.0021	-1769.26	0.00
WRL	0.0388	19612.599	0.00
TotalRD	0.0302	712981.63	0.00
WTotalRD	0.1778	2495638.07	0.00
TotalRDsq	-5.16E-09	-0.0159	0.987

Note: TotalRD means aggregate R&D expenditure; WTotalRD is its spatial lag term.

Table 5: Variable coefficient estimate of aggregate R&D expenditure

	K	L
Min.	0.2464	0.1882
1st quartile	0.2509	0.1912
Median	0.2536	0.1923
Mean	0.253	0.1924
3rd quartile	0.2549	0.1938
Max.	0.2584	0.1958

(2) Government R&D expenditure

Using the MGWPR-SDM(1,0,kv) model, we can estimate the effect of government R&D investment on economic growth (Table 6). The coefficient of elasticity of GovRD is negative in all quantiles, and the coefficients of the square term of government R&D investment are all positive. These values indicate that government R&D investment has a U-shaped impact on economic growth. This U-shaped impact may be because government R&D investment mainly targets basic research, and economic benefits cannot be obtained immediately. However, with an increase of government R&D investment, this investment has a positive impact on economic growth. Judging from the regional distribution of the GovRD coefficient (Figure 2), the government's initial investment in R&D has the greatest negative impact on the northeast region, gradually weakening from northeast to southwest. Thus, the Swedish paradox shows spatial heterogeneity.

Table 6: Variable coefficient of government R&D expenditure

	Intercept	wgdp	K	L	rl	wrl	GovRD	GovRDsq
Min.	-4.08E-17	0.5995	0.2033	0.1533	0.02121	-0.06421	-0.014965	2.82E-07
1st quartile	-3.39E-17	0.621	0.2095	0.1539	0.02392	-0.04097	-0.011611	3.18E-07
Median	-3.19E-17	0.6293	0.2135	0.1543	0.02491	-0.0317	-0.010476	3.36E-07
Mean	-3.22E-17	0.6277	0.2131	0.1546	0.02509	-0.02629	-0.010475	3.37E-07
3rd quartile	-2.94E-17	0.635	0.2159	0.1551	0.02652	-0.01087	-0.009146	3.55E-07
Max.	-2.53E-17	0.6452	0.2227	0.1574	0.02993	0.02518	-0.00717	3.92E-07

Note: “GovRD” means government R&D expenditure; “GovRDsq” is its square term.

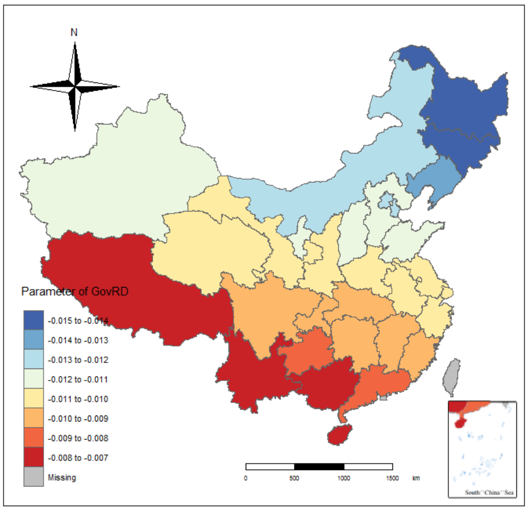


Figure 2: Spatial heterogeneity of government R&D expenditure coefficients

(3) Business enterprise R&D expenditure

As Table 7 shows, the business enterprise R&D expenditure in all quantiles has a positive effect on economic growth, and the higher the quantile is, the greater the impact will be. From the perspective of regional distribution (Figure 3), the elasticity coefficient of corporate R&D expenditure to economic growth gradually increases from south to north. Each 1% increase in corporate R&D expenditure in the southern region has a smaller percentage increase in GDP than in the north.

Table 7: Variable coefficient of business enterprise R&D expenditure

	K	L	EnterRD
Min.	0.2088	0.09494	0.07793
1st Qu.	0.2126	0.09971	0.07921
Median	0.2152	0.10181	0.07971
Mean	0.2149	0.10174	0.07966
3rd Qu.	0.2166	0.10379	0.08036

Max.	0.221	0.10833	0.08074

The negative coefficient of EnterRDsq suggests that there may be an inverted U-shaped relationship between enterprise R&D expenditure and economic growth. Accordingly, the impact of enterprise R&D expenditure on economic growth is positive at the beginning, and the Swedish paradox exists after a certain threshold is reached. Business enterprise R&D expenditure is a subdivision of aggregate R&D expenditure. Therefore, we can conclude that this form of expenditure is the decisive factor that leads to the U-shaped influence of aggregate R&D expenditure on economic growth. In addition, the coefficient of the spatial lag item WEnterRD of business enterprise R&D expenditure is negative. This result indicates that an increase in business enterprise R&D expenditure in the immediate area hinders the economic growth of the region, perhaps because of mutual competition.

Table 8: Fixed coefficient estimate of business enterprise R&D expenditure

Variable	Coefficient	*t* value	*p* value
WY	0.2295	361441.559	0.00
RL	-0.1220	-6081884.207	0.00
WRL	0.1176	760804.589	0.00
WEnterRD	0.0653	11091631.2	0.00
EnterRDsq	-7.56E-09	-0.25787477	0.79

Note: “EnterRD” means business enterprise R&D expenditure; “WEnterRD” is its spatial lag term; “EnterRDsq” is its square term.

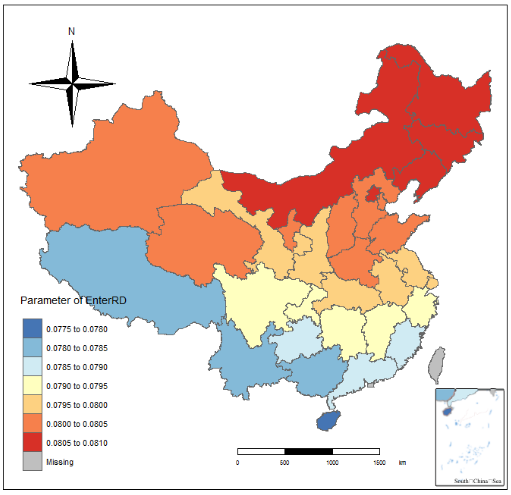


Figure 3: Spatial heterogeneity of business enterprise R&D expenditure coefficients

(4) R&D intensity

In addition to the two subdivisions of R&D expenditure (government R&D expenditure and business enterprise R&D expenditure), we also analyzed the impact of R&D intensity (R&D expenditure/GDP) on China’s economic growth. The results of the MGWPR-SDM (1,0, kv) model (Table 9) show that the coefficients of R&D intensity (Inten) are all negative. By contrast, the coefficients of the square term (Intensq) are mostly positive, indicating R&D intensity. The impact on economic growth is U-shaped. As R&D intensity increases, its impact on economic growth changes from negative to positive. From the perspective of regional distribution (Figure 4), the coefficient of Inten gradually increases from northeast to southwest. The three provinces in northeast China experience the largest negative impact, and the negative impact in Tibet is the weakest. The coefficients of Intensq (Figure 5) for all provinces and cities except Tibet and Xinjiang are positive numbers that decrease from northeast to southwest. Generally, increasing the intensity of one unit has the greatest impact on economic growth in the northeast and has the least impact on economic growth in the southwest, especially Tibet.

Table 9: Variable coefficient of R&D intensity

	Intercept	wgdp	K	L	rl	wrl	Inten	wInten	Intensq
Min.	-9.00E-18	0.47	0.1895	0.1885	0.2156	-0.1581	-0.2559	0.2434	-0.001066
1st Qu.	-4.55E-18	0.4955	0.1939	0.1901	0.2224	-0.12736	-0.2379	0.2474	0.001421
Median	-2.60E-18	0.5071	0.1967	0.1904	0.2254	-0.1151	-0.2314	0.2506	0.003059
Mean	-2.37E-18	0.5048	0.1961	0.1904	0.2257	-0.11123	-0.2306	0.2509	0.002725
3rd Qu.	-1.19E-18	0.5142	0.198	0.1909	0.2291	-0.09253	-0.2215	0.2528	0.003838
Max.	3.47E-18	0.5279	0.2019	0.1912	0.2367	-0.05528	-0.2035	0.2678	0.005836

Note: “Inten” means R&D intensity; “WInten” is its spatial lag term: “Intensq” is its square term.

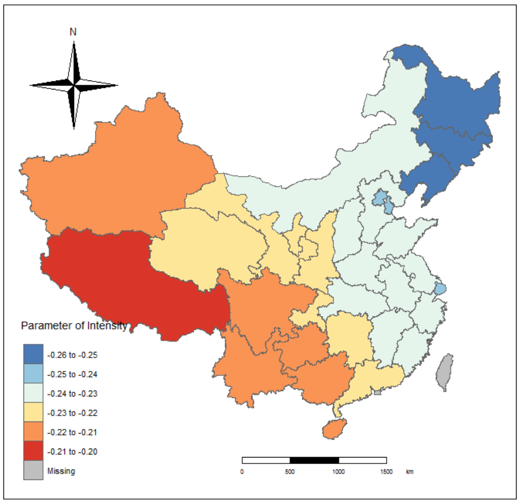


Figure 4: Spatial heterogeneity of government R&D expenditure coefficients

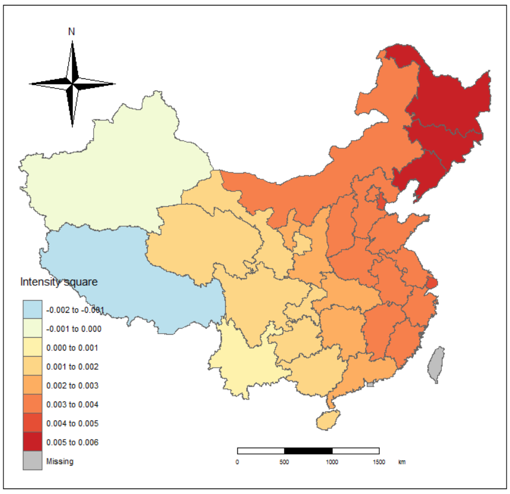


Figure 5: Spatial heterogeneity of R&D intensity square term

5.Conclusions

This paper provides a new, generalized model of spatial heterogeneity (MGWPR-SDM). We use this model to analyze Chinese provincial data from 2013 to 2017. This model responds to scholars' questions over whether R&D investment promotes China's economic growth. That is, the study explores whether there is a Swedish paradox in China.

The conclusions are as follows. First, the impact of aggregate R&D expenditure on China's economic growth follows an inverted U-shaped curve. This impact is positive at the beginning and negative beyond a certain threshold. The aggregate R&D expenditure in neighboring regions also has a positive impact on the region. Second, the impact of R&D intensity on economic growth is also U-shaped (except for Xinjiang and Tibet). Its negative effect gradually decreases from northeast to southwest before reaching the threshold. Third, government R&D investment, which is one of the components of aggregate R&D expenditure, has a U-shaped impact on regional economic growth. By contrast, the impact of enterprise R&D expenditure on economic growth also follows an inverted U-shaped curve. This impact is the main reason for the inverted U-shaped impact of aggregate R&D expenditure on economic growth. Both of these two effects have spatial heterogeneity. The Swedish paradox exists before the threshold of government R&D investment and after the threshold of enterprise R&D expenditure. In short, the conclusion of this study is that there is indeed a Swedish paradox in China but that it depends on the kind of R&D expenditure and the stage of this expenditure.

Therefore, the policy implication is that when formulating policies, the government should analyze specific problems. The government should also fully consider spatial heterogeneity, and the special conditions of various regions, such as geographical location and human capital level. Government-led basic R&D investment should be increased. Such an increase would benefit not only future R&D development but also society as a whole, including private enterprises, because of spatial externality.

Meanwhile, business enterprise R&D investment should be controlled on a moderate scale. Excessive R&D expenditure is unfavorable to economic output, as well as leading to efficiency losses and resource waste, thereby reducing the competitiveness of enterprises. Both the government and enterprises should make R&D investment that matches local conditions.

The shortcomings of this paper offer opportunities for future research. First, to further explore the threshold effect of R&D expenditure on economic growth in space, time, and related variables, a geographically weighted regression (GWR) cluster model and a threshold model must be combined. Second, a GWR cluster model should be combined with a spatial structural equation model (SESEM). We could thus not only consider multiple substitution variables of R&D input but also study the mediating effect of R&D expenditure on economic growth and deeply analyze the spatial heterogeneity of the influence of R&D expenditure on economic growth through innovation and spatial clustering. Third, the combination of MGWPR, a spatial error model (SEM), and a spatial lag of X model (SLX), namely the MGWPR-SEM and MGWPR-SLX models, is still unexplored, providing important future research directions. Fourth, the impact of R&D expenditure on economic growth changes not only with geographical location but also with time. Therefore, building a spatiotemporal variable coefficient model is more in line with the actual situation.

Appendix A: Estimation of the MGWPR-SDM model

(1) When , and ρ is a variable coefficient, the estimation of the MGWPR-SDM model is as follows:

Step 1: Assume that the fixed coefficients λ_c are known. Then,

$$\begin{aligned} Y - X_c\lambda_c &= \rho_{(u_i,v_i)}WY + X_v\lambda_{v(u_i,v_i)} + \varepsilon \\ Y^* &= \rho_{(u_i,v_i)}WY + X_v\lambda_{v(u_i,v_i)} + \varepsilon \qquad (11) \\ &= Z\delta_{(u_i,v_i)} + \varepsilon \end{aligned}$$

where $Y^* = Y - X_c\lambda_c$, $Z = (WY, X_v)$, and $\delta_{(u_i,v_i)} = (\rho_{(u_i,v_i)}, \lambda_{v(u_i,v_i)})'$. At this point, Eq. (11) changes into the ordinary GWPR model. The spatial lag term of the dependent variable is contained in Z, so $\mathrm{cov}(WY, \varepsilon \neq 0)$. Therefore, OLS cannot provide a consistent and effective estimator. Referring to the estimation methods of Baltagi (2011) and Jaya et al. (2018), this paper uses the spatial two-stage least squares (2SLS) method with the generalized moment estimation of Kelejian (1998) to estimate the variable coefficient $\delta_{(u_i,v_i)}$:

$$\hat{\delta}_{(u_i,v_i)} = (\hat{Z}'G\hat{Z})^{-1}\hat{Z}'G(Y - X_c\lambda_c) \qquad (12)$$

where, $\hat{Z} = P_H Z = (\widehat{WY}, X_v)$, $\widehat{WY} = P_H WY$, $P_H = H(H'H)^{-1}H'$, the instrumental variable (IV) matrix H is a matrix composed of linearly independent columns of $(X_v, WX_v, W^2X_v, ..., W^qX_v)$, and q is usually taken as 2. Further available estimates are:

$$\hat{Y}^*_{it} = Z_{it}\hat{\delta}_{(u_i,v_i)} = Z_{it}(\hat{Z}'G\hat{Z})^{-1}\hat{Z}'GY^* = SY^* = S(Y - X_c\lambda_c) \qquad (13)$$

where $G = G_{(u_i,v_i)} \otimes I_T$, I_T is the T-dimensional identity matrix, and $G_{(u_i,v_i)} = diag(G_{(u_1,v_1)}, G_{(u_2,v_2)}, ..., G_{(u_n,v_n)})$ represents the spatial weight composed of the distance between the i^{th} place and other places, whose value gradually decreases with distance. Usually, there are three kinds of spatial weight $G_{(u_i,v_i)}$ in the GWR model:

$$Gaussian: G_{(u_i,v_i)} = \exp(-0.5(d_{ij}/h)^2)$$

$$Bisquare: G_{(u_i,v_i)} = \begin{cases} (1-(d_{ij}/h)^2)^2, & when\ d_{ij} \le h \\ 0 & , when\ d_{ij} > h \end{cases}$$

$$Tricube: G_{(u_i,v_i)} = \begin{cases} (1-(d_{ij}/h)^3)^3, & when\ d_{ij} \le h \\ 0 & , when\ d_{ij} > h \end{cases}$$

where $d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$ represents the spatial distance between locations *i* and *j*, and *h* is the bandwidth. In this paper, gaussian space distance weights are used. These are the most commonly used weights in the literature. The selection of optimal bandwidth *h* can be determined by minimizing the AICc quasi-side, BIC, or cross-validation (CV) method and Mallows' law (Brunsdon et al. 1996 1999; Fotheringham et al., 2003). The minimization AICc method is adopted here.

$$h_1 = \arg\min \ AICc(h)$$

$$AICc = \log\left[\frac{1}{n} RSS(h)\right] + \frac{n + tr(S)}{n - 2 - tr(S)}$$

Each block matrix in Eq. (13) is: $S = (S_1, S_2, ..., S_t)'$

$$S_t = \begin{pmatrix} Z_{1t}^{'}(Z'G_{(u_1,v_1)}Z)^{-1}Z'G_{(u_1,v_1)} \\ \vdots \qquad \ddots \\ Z_{nt}^{'}(Z^{'}G_{(u_n,v_n)}Z)^{-1}Z^{'}G_{(u_n,v_n)} \end{pmatrix}$$

Step 2: estimate the fixed coefficient λ_c. Substituting Eq. (13) into Eq. (11) gives:

$$(I - S)Y = (I - S)X_c\lambda_c + \varepsilon \qquad (14)$$

Let $Y^\circ = (I - S)Y$, and $X^\circ = (I - S)X_c$, then Eq. (14) can be further simplified to:

$$Y^\circ = X^\circ \lambda_c + \varepsilon \qquad (15)$$

Then Eq. (15) becomes a panel regression model. If the explanatory variables are exogenous, the OLS method can be used to solve the fixed coefficient in the model that does not change with geographical location:

$$\begin{aligned} \widehat{\lambda}_c &= (X^{\circ T} X^\circ)^{-1} X^{\circ T} Y^\circ \\ &= [X_c^{\ T}(I - S)^T (I - S)X_c]^{-1} X_c^{\ T}(I - S)^T (I - S)Y \end{aligned} \qquad (16)$$

If the explanatory variables X_c contain endogenous explanatory variables, the spatial 2SLS method can be used to solve:

$$\begin{aligned} \widehat{\lambda}_c &= (X^{\circ T} P_F X^\circ)^{-1} X^{\circ T} P_F Y^\circ \\ &= [X_c^{\ T}(I - S)^T P_F (I - S)X_c]^{-1} X_c^{\ T}(I - S)^T P_F (I - S)Y \end{aligned} \qquad (17)$$

where $P_F = F(F'F)F'F$, and F is the instrumental variable matrix. Since entrepreneurship is an endogenous explanatory variable, Eq. (17) is applicable. Substituting Eq. (16) or Eq. (17) into Eq. (12), gives the coefficients of the model that change with geographical location. Combined with Eq. (12) and Eq. (16), the final solution of the model MGWPR-SDM(1,k_c,k_v) is:

$$\begin{cases} \widehat{\lambda}_c = [X_c'(I - S)'(I - S)X_c]^{-1} X_c'(I - S)'(I - S)Y \\ \widehat{\delta}_{(u_i,v_i)} = (\widehat{Z}'G\widehat{Z})^{-1}\widehat{Z}'G(Y - X_c\widehat{\lambda}_c) \end{cases} \qquad (18)$$

Here, the first column in the coefficient matrix $\widehat{\delta}(u_i, v_i)$ is the estimated value of the spatial autocorrelation coefficient ρ , and the remaining part is λ_c .

(2) When ρ ≠ 0, and ρ is a constant coefficient, estimation of the MGWPR-SDM model is as follows:

$$Y = \rho WY + X_c\lambda_c + X_v\lambda_{v(u_i,v_i)} + \varepsilon \qquad (19)$$

Step 1: Merge the invariant coefficient terms in the model (i.e., combine variables WY and X as variables Z). Then Eq. (19) can be simplified as:

$$Y = Z\delta + X_v\lambda_{v(u_i,v_i)} + \varepsilon \qquad (20)$$

Assuming ρ and λ_c are known (i.e., δ is known), then Eq. (20) is converted into a standard GWPR model:

$$Y - Z\delta = X_v\lambda_{v(u_i,v_i)} + \varepsilon \qquad (21)$$

If all variables included in X_v are exogenous explanatory variables, then the estimated variable $\lambda_{v(u_i,v_i)}$ coefficient can be obtained by solving (21) :

$$\hat{\lambda}_{v(u_i,v_i)} = (X_v{}^T G X_v)^{-1} X_v{}^T G(Y - Z\delta) \qquad (22)$$

where $G = G_{(u_i,v_i)} \otimes I_T$, I_T is the *T*-dimensional identity matrix, and $G_{(u_i,v_i)} = \mathrm{diag}(G_{(u_1,v_1)}, G_{(u_2,v_2)}, \ldots, G_{(u_n,v_n)})$ represents the spatial weight composed of the distance between the i^{th} place and other places, whose value gradually decreases with distance. There are usually three options: Gaussian, Bisquare, and Tricube. All depend on the bandwidth *h*. The selection of the optimal bandwidth *h* can be determined by minimizing the AICc quasi-side, BIC, or cross-validation (CV) method and Mallows' law (Brunsdon et.al., 1996 1999; Fotheringham et al., 2003). In this paper, the minimization AICc method is adopted.

If some endogenous explanatory variables are included in X_v, then according to the estimation method of Jaya et al. (2018), the estimator of the variable coefficient $\lambda_{v(u_i,v_i)}$ can be obtained by solving (21):

$$\hat{\lambda}_{v(u_i,v_i)} = (\tilde{X}_v{}^T G \tilde{X}_v)^{-1} \tilde{X}_v{}^T G(Y - Z\delta) \qquad (23)$$

where $\tilde{X}_v = P_F X$, $P_F = F(F'F)^{-1}F'$, and F is the instrumental variable matrix. According to the above analysis, since entrepreneurship is an endogenous variable coefficient variable, Eq. (23) is applicable.

Step 2: Further simplify Eq. (21) to:

$$Y^* = X_v\lambda_{v(u_i,v_i)} + \varepsilon \qquad (24)$$

where $Y^* = Y - Z\delta$ and the estimation of the right is:

$$\hat{Y}^*_{it} = X_{vit}\hat{\lambda}_{v(u_i,v_i)} = X_{vit}(X_v{}^T G X_v)^{-1} X_v{}^T G Y^* = SY^* = S(Y - Z\delta) \qquad (25)$$

Each block matrix $S = (S_1, S_2, \ldots S_t)'$ in Eq. (25) is:

$$S_t = \begin{pmatrix} X_{v1t}{}^T (X_v{}^T G_{(u_1,v_1)} X_v)^{-1} X_v{}^T G_{(u_1,v_1)} \\ \vdots \qquad\qquad \ddots \\ X_{vnt}{}^T (X_v{}^T G_{(u_n,v_n)} X_v)^{-1} X_v{}^T G_{(u_n,v_n)} \end{pmatrix}$$

By substituting Eq. (25) into Eq. (24), it can be converted into an ordinary panel regression model:

$$(I-S)Y = (I-S)Z\delta + \varepsilon \tag{26}$$

Since WY in Z is an endogenous variable such that $E(WY,\varepsilon) \neq 0$, then the generalized space 2SLS method should be used to estimate the fixed coefficient matrix as:

$$\hat{\delta} = [Z'(I-S)'P_H(I-S)Z]^{-1} Z'(I-S)'P_H(I-S)Y \tag{27}$$

where $P_H = H(H'H)^{-1}H'$, the tool variable (IV) matrix is a matrix composed of linearly independent columns of $(X_c, WX_c, W^2X_c, \ldots, W^qX_c)$, and $q = 2$ is usually taken.

Let $Z^* = (I-S)Z$, $Y^* = (I-S)Y$, $\hat{Z}^* = P_H Z^*$. Then Eq. (27) can be further simplified to:

$$\hat{\delta} = [\hat{Z}^{*T}\hat{Z}^*]^{-1}\hat{Z}^{*T}Y^* \tag{28}$$

Combined with Eq. (23) and Eq. (27), the solution of model (19), $MGWPR-SAR(0,k_c,k_v)$, is:

$$\begin{cases} \hat{\delta} = [Z'(I-S)'P_H(I-S)Z]^{-1} Z'(I-S)'P_H(I-S)Y \\ \hat{\lambda}_{v(u_i,v_i)} = (\tilde{X}_v{}^T G \tilde{X}_v)^{-1} \tilde{X}_v{}^T G(Y - Z\delta) \end{cases} \tag{29}$$

The first column in the coefficient matrix is the estimated value of the spatial autocorrelation coefficient, and the remaining part is $\hat{\lambda}_c$.

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