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NEXUS BETWEEN FINANCIAL DEVELOPMENT, FDI, INDUSTRIAL STRUCTURE CHANGE AND INNOVATION IN THE POST-FINANCIAL CRISIS ERA: EVIDENCE FROM CHINA

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Abstract. China began to strive for innovation-driven economic growth by encouraging technological progress since the recent world financial crisis. Further, Chinese economy exhibited several different features since the crisis. Its financial credits surged. Meanwhile, it began to adjust its industrial structures. In order to test the effect of these policies, this paper investigates whether financial development, FDI and industrial structure changes affect innovation in this new era. The results find that provincial variation in innovation performance enlarged during this period. Further, financial development significantly improves innovation. However, FDI hampers innovation. Lastly, industrial structure adjustment promotes innovation. The paper suggests that China improve the technological skills of local firms and its human capital and introduce high-quality and efficient foreign direct investment to achieve an innovation-driven economic growth.

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1. Introduction

China aims to become an innovation-driven economy. It has issued an ambitious policy in 2006: The National Medium-and Long-Term Program of Science and Technology Development (2006–2020), which strives to enhance China's scientific and technological (S&T) progress, and to achieve an innovation-oriented economy by 2020. Many measures were taken to support technological innovation since then so that innovation could contribute to 70% of economic growth. Understanding what factors contributed to China's innovation is of predominant role to achieve an innovation-oriented economy.

Finance is key to innovation. Financial development (FD) may contribute to innovation, essentially through pooling necessary capital and then allocating them to innovative projects, through risk diversification and risk amelioration, and through alleviating information asymmetry. On the other hand, financial development may also hamper innovation. The expanding of financial sector may cause "brain drain" between industries so that financial resources are not allocated to the most productive uses and hamper innovation [8].

Keywords. Spatial econometric model, innovation, financial development, FDI, industrial structure.

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FDI is an important source of knowledge and technology for developing countries' innovation. FDI can affect a country's innovation through three channels. First, FDI firms are usually more advanced in their technologies, production organization methods, management experiences, and so on. By competing with those foreign rivals, domestic firms can learn from and imitate the rivals and finally improve their technology levels. This is the technology spillover effect. Second, FDI rivals makes the technologies of domestic firms obsolete. Domestic firms have to adopt more advanced technologies to better compete with foreign rivals: They must innovate and improve their technology levels to survive in the market. This is the competition effect. Third, the upstream and downstream linkages between FDI and domestic firms often force or lead the latter to improve the quality of their outputs and technology to meet foreign customer's needs.

The first motivation of our paper stems from the 2008 global financial crisis, which had a significant impact on China. Its exports decreased dramatically, and firms went into difficult times struggling for survival and profit. Financial development boomed, and credit expanded greatly since then. China's financial system has expanded dramatically since the recent world financial crisis. The value-added of the financial industry rose from 1834.56 billion in 2008 to 7625.06 billion yuan in 2019, with the ratio of its value-added to GDP rising from 6.1 in 2008 to 23.1 in 2020. Simultaneously, more employment is provided by the financial industry: the finance industry employment accounted for 0.54% in 2008 and 1.14% in 2020. Banking system assets rose by 203.63 trillion yuan from 2008 to 2020, and China became the largest banking system in the world in 2017 and has seen its banking assets quadruple in size since the 2007 financial crisis [33]. China's expanding credit and financial sector are arousing widespread worries that its financial sector is too overly expanding to be good [33]. Since finance can either benefit or harm innovation, we are interested in this question: what is the impact of China financial development on innovation after the recent world financial crisis?

The second motivation for our research comes from the fast growth of China's FDI. China has implemented a strategy of exchanging market for technology and encouraged foreign capital to invest directly in China in order to employ the foreign capital and learn from foreign advanced technology. Up to 2018, China has become the second largest country in the world in employing foreign capital, accounting for 10.7% of world foreign investments [35]. Since one of the primary purposes for China to attract FDI is to improve and enhance its domestic innovation, it is also interesting to ask: what is the effect of FDI on China's innovation, since FDI has grown to reach such a great volume?

The third motivation of our paper comes from the fact that Chinese government has rigorously pushed the adjusting and upgrading of its industrial structure since 2008. It advocates the development of the tertiary industry and the service industry. The change in industrial structure could have an impact on innovation [30, 38]. Industrial upgrading may deepen the division of labor. Driven by the improvement of the degree of specialization and the deepening of the division of labor, new products and services and business modes tend to emerge. Nowadays, China's tertiary industry has been playing an increasingly important role in China's economic development, thanks to the Chinese government policy of vigorously adjusting industrial structure and developing the tertiary industry. Hence, it is also of great significance to study the impact of industrial structure change on innovation since 2008.

The contribution of this paper is threefold. First, this is the first paper, to the best of our knowledge, which studies the nexus between FD, FDI, and industrial structure changes on innovation in China specifically during the post-crisis recession era. Although many papers study the effect of either FD or FDI on innovation, they do not address this issue specifically after the recent world financial crisis. Second, there are scarce researches investigating the effect of industrial structure changes on innovation, and this paper strives to shed some light on this issue. The third feature is this paper applies a spatial econometric model to account for the spatial spillover effects.

The paper is organized as follows. Section 1 is the introduction. Section 2 is a brief literature review. Section 3 introduces the methods and data. The results are discussions are in section 4. The last section gives the conclusions and policy suggestions.

2. Literature review

2.1. Nexus between finance and innovation

Finance may both benefit and hamper innovation in nature. On the one hand, financial development may contribute to innovation, through capital pooling and allocating, through risk diversification and amelioration, and through alleviating information asymmetry [12]. On the other hand, financial development may also hamper innovation. Essentially, the expanding of financial sector may cause "brain drain" between industries [8]. That is, finance may show its dark side on resource allocation as it develops, both on physical and human capital [9]: an overly expanding financial sector or credit may attract and induce both physical and human capital away from productive real sectors and into less productive sectors like the financial and real estate sector for pursuit of higher profits or wages. As a result, capital formation in the real sector is hurt, and firm productivity growth and innovation are dampened.

The positive role of FD on innovation has been verified by many researchers [1,3,5,6,20,21]. [39], using data of 50 countries from 1990 to 2016, find that the overall effect of FD on innovation is positive; however, this effect is lower when FD exceeds a certain level. [29], based on 22 manufacturing industries in 18 OECD countries, find that domestic financial development is an important determinant of R&D intensity. [20], according to data of 120,000 mainly unlisted Chinese firms, find that Chinese firms' innovation activities are constrained by the availability of internal finance. [37] show that short-term banking finance plays significantly positive roles in financing innovation investment both for SOEs and for non-state and foreign firms. However, many researches find evidence that finance hinders innovation [4, 8–10, 16, 24, 39]. For example, [9] finds that financial growth disproportionately harms the industries whose tangible assets are less or who are more R&D intensive. Empirical evidence from China include [34], who find that financial institution loans exert a significant negative effect on substantive and strategic innovation.

2.2. Nexus between FDI and innovation

FDI may contribute to a region's innovation through effects of imitation, competition, and technical and human capital spillovers to the host country. However, these effects occur only when domestic firms are not so outdated or backward in technology compared with foreign firms so that they have the ability to absorb the foreign advanced knowledge or skills or technology. Otherwise, host country firms will be forced to even lower value-added production, lower profits, or even go bankrupt. Therefore, whether FDI could benefit local innovation depends on host country firms' absorptive ability.

The empirical evidence on the relationship between FDI and innovation is also controversial. Some find FDI contributes to a region's innovation. For example, [31] find that FDI in China promotes innovation of China's electronic firms. [2] find FDI is positively related to patents of the Italian service industry. While some find FDI hampers local innovation. [17] find FDI in China negatively relates to SOEs' innovation. Still others, like [27], suggest that the relationship between FDI and innovation may be complex so that there may be non-linearities or threshold effects.

2.3. Nexus between industrial structure and innovation

The industrial structure of a region and its changes do affect the rate and the direction of innovation and technological change [2, 11, 30]. Changes in industrial structure are in effect the changes in either the quantity or scale of firms in different industries. More specifically, they are the expansion or contraction of productive abilities, usually production inputs such as human and physical capital, in different industries. In an inefficient market, motivated or promoted by government industrial policy, production factors in the second industry may flow into the tertiary industry. If the productive factors flow into more innovative firms and projects than before the industrial policy, then innovation would be improved as a result; otherwise, innovation would be hampered if the productive factors flow into less innovative firms or projects. Hence, whether changes in industrial structure will hamper or benefit innovation depends on where the scarce productive resources flow into. That is, whether there is brain drain between industries.

There are few studies on the impact of industrial structure changes on innovation. Among the few, [30] find that the shift from secondary industry toward tertiary industry does not contribute to improving marine technological innovation. [38] find, using data of 30 Chinese provinces from 2000-2016, that industrial structural rationalization can promote all kinds of directed technological progress at the national level. Further, they find industrial structural upgrading and ecologicalization promote fossil fuel efficiency and environmental efficiency.

3. Methodology, data, and model specification

3.1. Data

Our data cover annual data of China's 30 provinces[3] (excluding Hong Kong, Tibet, Macao, and Taiwan for lack of data) from 2008 to 2020. All the data were compiled from EPS. FD, FDI, and GDP were deflated by 2005 level.

3.2. Calculating provincial innovation

Two categories of indicators are commonly used most to represent innovation: input indicators, such as R&D input, and output indicators, such as patents, new product sales. Many believe that output indicators are more suitable than input indicators [17, 20]. Among the output indicators, new product sales has two major limitations. The first is that it does not include the innovation of processing process, which can improve the production technology of existing products. The second is that it is subject to business cycles. While, the number of patents granted is a widely adopted in literature [19, 28], which includes the process innovation and product innovation and is somewhat in between patent applications and new product sales. Therefore, we use provincial patents granted, or patent authorizations, to proxy (PAT) for provincial innovation. The other two indicators, patent applications and new product sales, are used for robustness checks.

3.3. Dynamic evolution of provincial innovation

Kernel density estimation is applied to explore the spatial distribution and dynamic evolution of innovation performance.

$$\widehat{f}(x_0) = \frac{1}{nh} \sum\nolimits_{i=1}^{n} K\left[(x_i - x_0)/h\right]. \tag{3.1}$$

Where n is the number of samples, with $n = 30$ in this paper. $K(\cdot)$ is the Kernel function, which is a weight function in nature. h is the band width. The optimal band width is determined by equation (3.2) .

$$h^* = \delta \left[\int_{-\infty}^{+\infty} f''(x_0)^2 dx_0 \right]^{-0.2} n^{-0.2}. \tag{3.2}$$

Where$f''(x_0)$ is the curvature of the Kernel density, and the constant $\delta \equiv \left[\int_{-\infty}^{+\infty} K(z)^2 dz / \left(\int_{-\infty}^{+\infty} z^2 K(z)\, dz \right)^2 \right]^{0.2}$ is dependent only on the Kernel density function.

[3]Currently, China has 23 provinces, four Centrally Administered Municipalities, five autonomous regions, and two special administered regions. As both the four Centrally Administered Municipalities, special administered regions and five autonomous regions are treated as provinces in China, they can all be referred to as provinces.

3.4. Measuring spatial auto correlation

Spatial auto correlation refers to the fact that the observed values of variables distributed among different areas may be dependent on one another. It reveals the spatial clustering or deviation of variables. As the first law of geology indicates: everything is related to everything else,but near things are more related than distant things. Moran's I measures the auto-correlation of variables. It has two most often used forms: global Moran's I and local Moran's I.

3.4.1. Spatial weight matrix

The spatial distance of different regions should first be measured and spatial weight matrix be given before applying Moran's I to measure the auto-correlation of variables. Our spatial matrix is defined according to equation (3.3).

$$W = \begin{pmatrix} w_{11} & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}. \tag{3.3}$$

Where n is the number of provinces, $n = 30$. $\{\mathrm{x}_i\}_{i=1}^{n}$ represents the spatial data of n provinces, with the subscript representing province i. w_{ij} is the spatial distance between province i and j. The diagonal in equation (3.3), w_{nn} shows the spatial distance between a province and itself, is zero. Hence, w_{11}=w_{22}=$\ldots$=w_{nn}= 0. While $w_{ij}(i \neq j)$ is the inverse or reciprocal of the squared geographical distance between two capital cities is used as the weight.

3.4.2. Global auto correlation

Spatial auto correlation illustrates that the same variable for adjacent areas often related to one another. Positive spatial auto correlation refers to the fact the same variable of adjacent areas takes on similar absolute values with the same signs, while negative spatial auto correlation refers to the fact the same variable of adjacent areas takes on similar absolute values with opposite signs. Global Moran's I measures the spatial clustering degree of serial $\{x_i\}_{i=1}^{n}$. The formula is equation (3.4).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}. \tag{3.4}$$

Where w_{ij} is the spatial weight matrix, here the weight is the reciprocal of the squared geographical distance between two provinces' capital cities; x_i and x_j are the values of the variable for province i and j respectively. $\bar{x}$ is the mean. Generally, Moran's I is between -1 and 1. When Moran's $I > 0$, there is positive spatial correlation; the larger the index value, the more obvious the spatial aggregation. When Moran's $I < 0$, there is negative spatial correlation; the larger the index value, the greater the spatial heterogeneity. Otherwise, Moran's $I = 0$, which means a random distribution.

Generally, standardized Moran's I follows the following normal distribution as expressed in equation (3.5).

$$I^{*} \equiv \frac{I - E(I)}{\sqrt{Var(I)}} \xrightarrow{d} N(0,1). \tag{3.5}$$

Where $E(I)$ is the mean of Moran's I, and $Var(I)$ is its variance. The critical value test for standard normal distribution could be used to test the significance of Moran's I.

3.5. Spatial panel regression model

Our dependent variable is provincial innovation, proxied by the number of patents granted. Our main explanatory variable is FD, FDI, and industrial structure change. Financial development is proxied by the loans of a province's financial institutions per unit of provincial GDP. This indicator is selected essentially for two reasons.

Table 1. List of variables and descriptions.

Symbols	Variable	Description
PAT	Innovation	Number of patents granted
FD	Financial Development	Loans of financial institutions/GDP
FDI	FDI	Provincial actual use of FDI/GDP
ISA	Industrial structure change	Provincial value-added of the secondary industry/GDP
RDPE	R&D personnel input	Full-time equivalent of R&D personnel by region
RDIE	R&D input	Intramural expenditures on R&D
GDP	Economic Growth	Provincial GDP

First, indirect financing is still the source of capital for firms in China. Second, many researches, such as [7], use this proxy. Second, although [26] suggest that private credit by banks and other financial institutions as a share of GDP is a preferred proxy for FD. As China does not publish private credit, loans of financial institutions are used instead. Industrial structure change is proxied by the proportion of the added value of the secondary industry in GDP, because China is in the stage of industrial structure optimization, vigorously developing the tertiary industry, while the secondary industry is shrinking. According to [18] and [22], the innovation performance is a function of innovation input, mainly R&D expenditure and R&D personnel inputs. Hence, our panel regression model also controls these two indicators. Further, GDP is also controlled.

Table 1 shows the specific meaning and details of the variables.

Hence, our regression model is specified as:

$$\begin{aligned} \ln PAT = \beta_0 + \beta_1 \ln FD + \beta_2 \ln FDI + \beta_3 \ln RDPE \\ + \beta_4 \ln RDIE + \beta_5 \ln ISA + \beta_6 GDP + \varepsilon. \end{aligned} \tag{3.6}$$

Where β_0 is the intercept, β_{1-6} is the coefficients of the explanatory variables, and ε is the random term.

As innovation is often spatially auto correlated due to its imitation and diffusion, spatial econometric model is selected as our regression model. There are three models commonly used in spatial panel data regression: spatial lag models (SLM), spatial error models (SEM) and spatial Durbin models (SDM). The spatial lag variable of the dependent variable is introduced into Spatial lag models as an explanatory variable, the spatial lag variable of the standard error is introduced into the spatial error models (SEM) as one explanatory variable, while both are introduced into the spatial regression model to be the spatial Durbin model. Hence, spatial Durbin models, expressed as equation (3.7), are in fact a general form of SEM and SLM, and could be reduced to SLM or SEM under certain conditions.

$$y_{it} = \lambda W y_{it} + X_{it}\beta + W X_{it}\delta + \psi_i + \varphi_t + \varepsilon_{it}. \tag{3.7}$$

Where: y_{it}-the dependent variable; X_{it}-the vector of explanatory variable; λ, δ-the coefficients of the spatial lag terms of the dependent variable and independent variable respectively; W-the geographical distance spatial weight matrix; β-the coefficients of the independent variables; ψ_i and φ_t-the intercepts of the spatial effect model and time effect model respectively; ε_{it}-the random error.

The spatial econometric model is specified as equation (3.8), according to equation (3.7)

$$\begin{aligned} &\ln PAT_{it} = \beta_0 + \beta_1 \ln FD_{it} + \beta_2 \ln FDI_{it} + \beta_3 \ln RDPE_{it} + \beta_4 \ln RDIE_{it} \\ &+\beta_5 \ln ISA_{it} + \beta_6 \ln GDP_{it} + \lambda W \ln INN_{it} + \delta_1 W \ln FD_{it} + \delta_2 W \ln FDI_{it} \\ &+\delta_3 W \ln RDPE_{it} + \delta_4 W \ln RDIE_{it} + \delta_5 W \ln ISA_{it} + \delta_6 W \ln GDP_{it} + \varepsilon_{it} \\ &\varepsilon_{it} = \lambda W \varepsilon_i + u_{it}, u_{it} \sim i.i.d(0, \sigma^2). \end{aligned} \tag{3.8}$$

Where i is the i-th province, $i = 1, 2, \ldots, 30$; t is time, $t = 1, 2, \ldots, 10$, being years from 2008 to 2020 respectively. If $\theta = 0$, then the SDM model expressed in equation (3.8) becomes a SLM; a SEM if $\theta + \delta\beta = 0$. Otherwise, it is the general SDM.

[25] proved that SDM could not estimate the marginal effects, as accurately as non-spatial models, of the explanatory variables. Hence they put forward a partial differential approach to estimate the marginal effects of the variables. [15] extended this method into SDM to derive the spatial spillover effects. Usually, the effect of an explanatory variable can be divided into direct and indirect effects. Transforming equations (3.7) and (3.9) is derived.

$$y_{it} = (\mathrm{I}-\lambda W)^{-1}(X_{it}\beta + WX_{it}\delta) + (\mathrm{I}-\lambda W)^{-1}\psi_i + (\mathrm{I}-\lambda W)^{-1}\varphi_t + (\mathrm{I}-\lambda W)^{-1}\varepsilon_{it}. \tag{3.9}$$

Equation (3.9) could be further transformed into the following matrix by differentiating it with respect to the k-th explanatory variable:

$$\left[\frac{\partial y}{\partial X_{ik}} \times \frac{\partial y}{\partial X_{Nk}}\right] = \begin{bmatrix} \frac{\partial y_1}{\partial X_{ik}} & \cdot & \frac{\partial y_1}{\partial X_{Nk}} \\ \cdot & \cdot & \cdot \\ \frac{\partial y_N}{\partial X_{ik}} & \cdot & \frac{\partial y_N}{\partial X_{Nk}} \end{bmatrix} = (I - \lambda W)^{-1} \begin{bmatrix} \beta_k & \omega_{12}\delta_k & \cdot & \omega_{1N}\delta_k \\ \omega_{21}\delta_k & \beta_k & \cdot & \omega_{2N}\delta_k \\ \cdot & \cdot & \cdot & \cdot \\ \omega_{N1}\delta_k & \omega_{N2}\delta_k & \cdot & \beta_k \end{bmatrix}. \tag{3.10}$$

Then, the mean of the diagonal elements for the k-th explanatory variable measures the direct effect of the k-th explanatory variable. Further, the mean of either the columns or rows, excluding the diagonal, in equation (3.10), represents the indirect effect of an explanatory variable. It represents the impact of the k-th explanatory variable on the dependent variable of adjacent areas, or the impact of the k-th explanatory variable of adjacent areas on local dependent variable; the total impact of the k-th variable is the sum of the indirect and direct effect.

4. Results and discussions

4.1. Dynamic evolution of China's provincial innovation

Four years: 2008, 2012, 2016 and 2020, are selected to estimate the Kernel density of provincial innovation, which are shown in Figure 1.

Figure 1 shows the dynamic evolution of innovation. First, the four core density curves and their peak values move to the right year by year, indicating that the innovation level of China's provinces has been continuously improving in recent years, and the peak values of the four curves have experienced a process of first decreasing and then increasing. Secondly, the peak of the kernel density curve in selected years becomes steeper, which indicates that the innovation level of the province presents spatial polarization. Third, compared with 2008, the left tail of the kernel density curve is shorter in 2020, which to some extent indicates that the provinces with relatively low innovation level are gradually decreasing. Fourthly, it can be seen from the figure that provincial innovation fell roughly within the range of 7–12.5 in 2016 and 8.4–13.4 in 2020, which indicates that although spatial polarization has eased and provincial innovation level has improved, the huge heterogeneity and differences of provincial innovation have reached an unprecedented degree.

4.2. Spatial distribution of China's provincial innovation

ArcGIS10.8 is applied to illustrating the spatial distribution of the 30 provinces' innovation in four selected years: 2008, 2012, 2016 and 2020 respectively. Provincial innovation levels are classified into five ranges, see Figure 2. One different color represents one different level; the darker the color, the higher the level of innovation.

The following can be evidence from Figure 2. First, overall, the four charts show that the innovation level of China's provinces has continued to improve after the financial crisis, with southern provinces having a higher innovation level than their northern counterparts. Second, provinces with higher innovation levels are mainly distributed in east, central and south China, with Guangdong leading the way. Meanwhile, innovation in

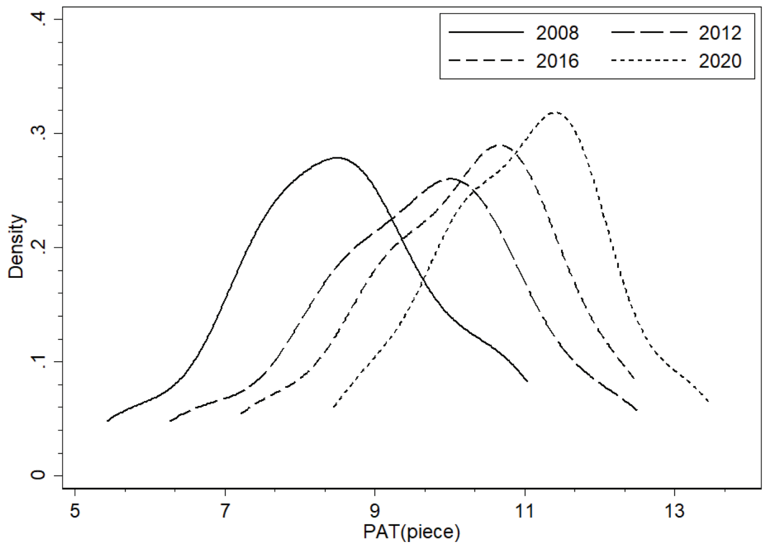

FIGURE 1. Kernel density plot of China's innovation in selected years.

western provinces is low. Third, the spatial distribution in 2012 shows that south and East China saw the fastest improvement in innovation. Since these provinces are also experiencing rapid economic growth, this should be related to the economic structure of these provinces, which may be the result of these provinces responding to the government's call to change the pattern of economic growth and improve innovation performance during this period. Fourth, overall, the southwest, east, south and central regions showed higher innovation levels, with Jiangxi, Fujian and Anhui showing the fastest improvement in innovation performance. To sum up, after 2008, the innovation level of provinces has improved on the whole, but there are significant differences between the north and the South, and the spatial differentiation and gap have been increasing.

4.3. Spatial auto-correlation of Chinese provincial innovation

StataMP 14 was used to calculate the Global Moran's I of provincial innovation, geographical-distance weighted, from 2008 to 2020. Figure 3 shows that Moran's I fluctuates between 0.24 and 0.33 during these 13 years and are all significant at the 1% significance level (Z-score are all greater than 2.95). This illustrates that Chinese provincial carbon intensity is spatially auto-correlated or spatially dependent, instead of randomly distributed. Therefore, spatial effects must be modeled when regressing the impact factors of China's provincial carbon intensity to obtain accurate results in agreement with the practice.

4.4. Results for spatial panel regression

4.4.1. Spatial model selection

The existence of spatial dependence between variables will be further confirmed before we choose appropriate spatial econometric models.

Firstly, Hausman test is carried out on the panel model without considering the spatial effect, and the result shows that the random effect model can be rejected at the significance level of 1%. Therefore, LM test should also be carried out on the basis of fixed effect model and ordinary panel model without fixed effect. Secondly, LM test should also be utilized on the ordinary fixed effect panel model and the no fixed effect panel model to further verify the existence of spatial effect. The results are shown in Table 2. The results show that all the four models reject the null hypothesis that there is no space lag effect or space error effect, which proves the existence of space effect. Therefore, the spatial econometric model will be used for our panel regression.

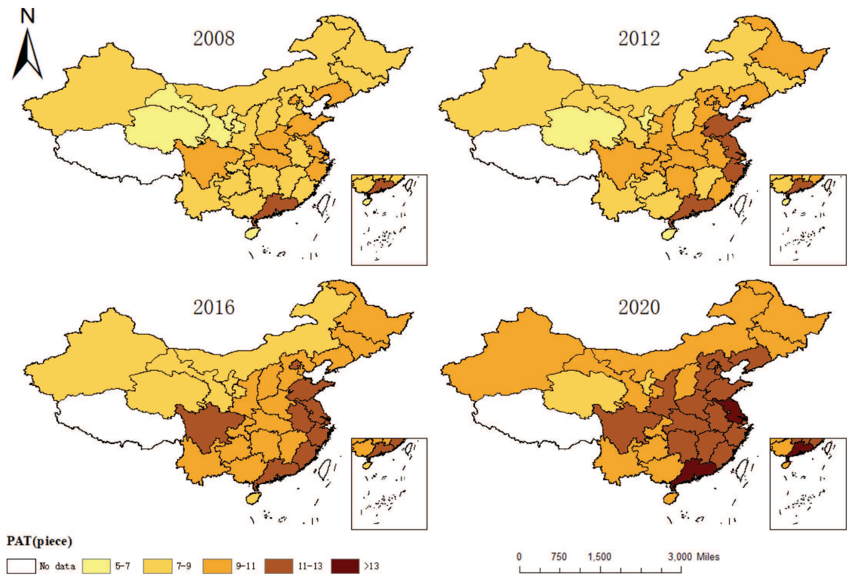

FIGURE 2. Spatial distribution of China's provincial innovation in selected years.

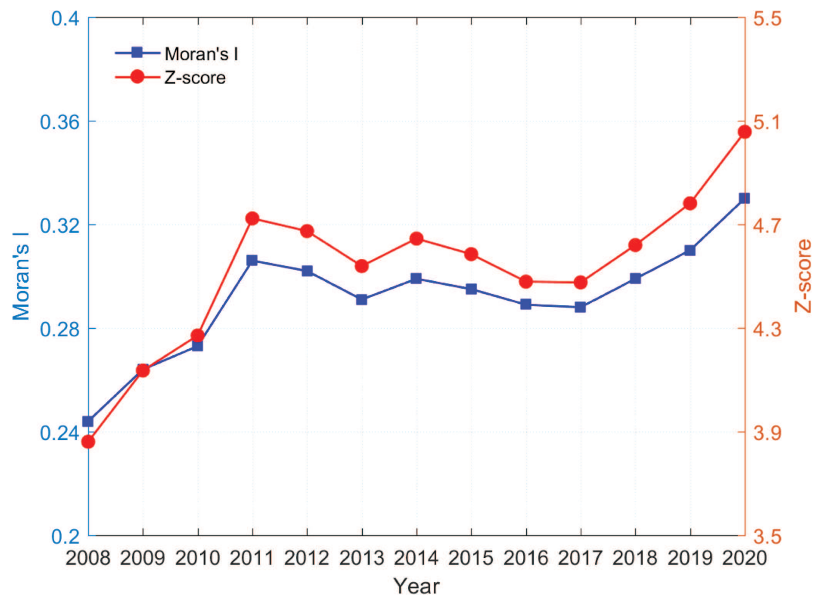

FIGURE 3. Global Moran's I values of China's provincial innovation during 2008–2020.

Comparing the test statistics of the four models for ordinary panel regression, it can be deduced that the R^2 and Adjusted R^2 of the no fixed effect model and the spatial fixed effect model are the highest, indicating that they give better fits. What's more, the LM-lag, LM-error, Robust LM-lag and Robust LM-error tests for the individual fixed effects model are all significant at a significance level of 5% or 10%; while the LM-lag test statistics of mixed effect model fail the robustness test at 10% significance level. Hence, the time fixed period fixed effects model is good. Further, some researches suggest fixed effects models are more appropriate and

TABLE 2. LM Test statistics for ordinary panel models when spatial effect is not controlled for.

Variable	No fixed effects	Spatial fixed effects	Time period fixed effects	Spatial and time period fixed effects
R^2	0.9459	0.9434	0.9281	0.9215
log-L	−153.3498	−144.9240	−125.6598	−115.4427
LM-lag	2.8903$^{(*)}$	6.4468$^{(**)}$	5.8681$^{(**)}$	4.6058$^{(**)}$
Robust LM-lag	2.0906	1.1536	2.9519$^{(*)}$	1.9392
LM-error	40.5404$^{(***)}$	41.6881$^{(***)}$	5.7760$^{(**)}$	5.7555$^{(**)}$
Robust LM-error	39.7387$^{(***)}$	36.3984$^{(***)}$	2.8597$^{(*)}$	3.0888$^{(*)}$

Notes. $^{(*),(**),(***)}$represent significance at 10%, and 5%, and 1% level respectively.

TABLE 3. Spatial Durbin Model estimation and test result.

Variable	Coefficient	Asymptot t-stat	Z-probability
LnFD	1.2074$^{(***)}$	16.1260	0.0000
LnFDI	−0.0404$^{(**)}$	−2.2165	0.0267
LnISA	−3.0684$^{(***)}$	−7.8160	0.0000
LnRDPE	0.3625$^{(***)}$	4.6077	0.0000
LnRDIE	0.3924$^{(***)}$	5.9216	0.0000
LnGDP	0.5537$^{(***)}$	7.8979	0.0000
WLnFD	−0.3518$^{(***)}$	−4.2293	0.0000
WLnFDI	−0.0145$^{(*)}$	−0.7445$^{(*)}$	0.0565
WLnISA	0.2512$^{(*)}$	0.7300$^{(*)}$	0.0654
WLnRDPE	−0.0081	−0.0940	0.9251
WLnRDIE	−0.0334	−0.4337	0.6645
WLnGDP	−0.1812$^{(***)}$	−2.7662	0.0057
Wdep.var.	0.1620$^{(***)}$	4.8200	0.0000
R−squared = 0.9547			
log−likelihood = −122.5146			
Wald−lag = 40.7095$^{(***)}$			
Wald−error = 16.9265$^{(***)}$			
LR−lag = 39.4870$^{(***)}$			
LR−error = 15.5756$^{(***)}$			

Notes. $^{(*),(**),(***)}$represent significance at 10%, and 5%, and 1% level respectively.

robust in economic regressions most of the time [23, 32]. Therefore, individual fixed effect model is selected as our panel regression model.

Hence, both the spatial auto-correlation analysis and the LM test validate the applicability of spatial econometric models. Thus, spatial Durbin model is employed to estimate the nexus between FD, FDI, industrial structure change and innovation. The estimation results are shown in Table 3. Table 3 shows R^2 of the spatial model is 0.9547, obviously enhanced relative to the original 0.9459 when spatial effects are not considered. Further, Wald-lag, Wald-error, LR-lag, and LR-error are all significant at 1% level. 0

4.4.2. Results of the marginal effects estimation

As these results of the spatial Durbin model could not show the marginal effects of the explanatory variables, formula (3.10) is applied to deriving the marginal effects which are shown in Table 4. The direct effects in Table 4 illustrates that a province's innovation is positively correlated with FD, internal expenditure of R&D

TABLE 4. Direct and indirect and total effects.

Independent variable	Direct effect coefficient	Indirect effect coefficient	Total effect coefficient
LnFD	$1.1864^{(***)}$	$-0.5474^{(**)}$	$0.6390^{(***)}$
LnFDI	$-0.0432^{(**)}$	$-0.0735^{(*)}$	$-0.1167^{(**)}$
LnISA	$-3.1048^{(***)}$	$-0.9344^{(*)}$	$-4.0392^{(***)}$
LnRDPE	$0.3689^{(***)}$	0.1725	$0.5413^{(***)}$
LnRDIE	$0.3964^{(***)}$	0.1138	$0.5102^{(***)}$
LnGDP	$0.5417^{(***)}$	−0.3284	$0.2133^{(***)}$

Notes. $^{(*),(**),(***)}$represent significance at 10%, and 5%, and 1% level respectively.

funds, and full-time equivalent of R&D personnel and GDP, while negatively correlated with FDI and industrial structure change. Further, FD, FDI and industrial structure change all have significant spatial spillover effects. Therefore, the overall effect supports the view that innovation is positively correlated with FD, R&D personnel investment, R&D investment and GDP, while negatively correlated with provincial industrial structure change and FDI.

4.4.3. Effect of FD on innovation

Table 4 shows that local FD significantly improves local innovation (at 1% significance level), and significantly curbs adjacent provinces' innovation (at 5% significance level). For every 1% increase in local FD, local innovation will be enhanced by 1.1864%, and adjacent areas innovation will be simultaneously decreased by 0.5474%, so that national innovation will be enhanced by 0.6390%.

The positive direct total effect of FD on innovation illustrates that financial resources are well managed so that they are desirably channeled into innovative projects. This shows that related national polices to increase science and technological inputs and improve innovation are well-executed to achieve the desired results in China. In spite of the 2008 financial crisis and on-going recession, China still managed to direct sufficient financial capital toward supporting innovation projects. This suggests that China's policy and related measures in encouraging innovation are fairly effective. This also implies that whether FD, or recession or financialization improves or hinders innovation may depend on the specific institutional environments.

4.4.4. Effect of FDI on innovation

The results show that FDI hinders local, neighbouring and overall innovation. As mentioned, Foreign direct investment has technology spillover effect and competition effect, with the former effect making domestic firms learn and imitate the foreign rivals' high and new technologies, and the latter effect making domestic firms undertake innovation to survive. Hence, the technology spillover effect of FDI prevails, and competition effect is absent in China. The result may suggest that Chinese domestic enterprises are still relatively behind foreign enterprises in technology, so domestic enterprises are squeezed out by FDI to a certain extent. Further, the status quo in China is that local firms simply imitate rather than innovate, so that FDI crowded out domestic firms innovation. On the one hand, due to the lack of innovation ability, domestic firms lose the market so that the market is occupied by foreign enterprises, which furtuer made domestic firms lose their innovation motivation. On the other hand, enterprises with strong innovation ability attract the most foreign direct investment, but the impact of foreign capital on innovation is not the highest.

Therefore, blindly introducing foreign capital is not the right choice for China at present. It is necessary to introduce high quality and high efficiency foreign direct investment to enhance the technology spillover effect and competition effect of foreign direct investment on regional innovation and promote regional innovation level. Hence, China should take measures to improve the R&D levels and innovation of domestic firms, so that there are enough competition in domestic market.

Table 5. Robustness test results.

	INN		PAA	
Variable	Coefficient	Asymptot t-stat	Coefficient	Asymptot t-stat
LnFD	0.4061$^{(***)}$	5.0043	1.0532$^{(***)}$	13.8869
LnFDI	−0.0326$^{(*)}$	−1.6527	−0.0288	−1.5601
LnISA	−0.8281$^{(*)}$	−1.9448	−3.1219$^{(***)}$	−7.8457
LnRDPE	0.4111$^{(***)}$	4.8187	0.3541$^{(***)}$	4.4421
LnRDIE	0.4120$^{(***)}$	5.7317	0.4445$^{(***)}$	6.6194
LnGDP	0.3318$^{(***)}$	4.3637	0.4421$^{(***)}$	6.2230

Notes. $^{(*)},^{(**)},^{(***)}$represent significance at 10%, and 5%, and 1% level respectively.

4.4.5. Effect of industrial structure change on innovation

The industrial structure change has a negative effect on local, neighboring and national innovation. As our industrial structure is proxied by the ratio of the second industry, the negative sign means a decrease in the ratio of the second industry and a simultaneous increase in the tertiary industry, which means industrial upgrading. Industrial upgrading may deepen the division of labor. Driven by the improvement of the degree of specialization and the deepening of division of labor, people are more familiar with their respective works and are at a better position to improve and innovate. As a result, learning by doing will prosper innovation and new products and services and business modes tend to emerge. Further, as the tertiary industry develops, new demands will emerge in the market, which means new opportunities for business. Firms will grasp these new opportunities by providing new products and services to satisfy the new demands, which requires firms to do continuous R&D to develop new products and further reduce the costs of these new products. This illustrates that China's policy of developing the tertiary industry succeeded in mobilizing productive resources into efficient and innovative firms or projects in the tertiary industry, which prospered innovation.

4.5. Robustness test

Related conventions are followed to test the reliability of our results [13, 14]. Two other indicators are used to substitute patents granted to proxy the dependent variable. The first is the new product sales revenue (INN) [36]. This index is measured by the ratio of new product sales revenue to GDP, which is deflated by the level of 2005. The second is the number of patent applications (PAA) which is measured as the logarithmic of the number of patent applications. The robustness test results in Tables 5 and 6 show that the two replacement indexes are significantly positively correlated with local FD, and negatively correlated with local FDI and local industrial structure change. The substitution variables again verify the previous results: financial development promotes innovation, while FDI and industrial structure change hinder innovation.

5. Conclusions and policy suggestions

5.1. Conclusions

This paper investigates, using provincial panel data, the relationship between FD, FDI, and industrial structure change and innovation in China after the recent world financial crisis. The following conclusions are derived. First, polarizing of provincial innovation has eased during the study period. Though, the provincial variation in innovation performance enlarged. Second, FD significantly improves both local innovation and national overall innovation level which shows financial resources are well managed. Third, local FDI hampers local innovation and national innovation, which suggests China's domestic firms are still relatively backward in technology compared with foreign firms, so that domestic firms' innovation capability are squeezed out to some extent by FDI. Fourth, industrial upgrading will be conducive to technological innovation.

TABLE 6. Direct and indirect and total effects.

	INN			PAA		
Variable	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
LnFD	0.4185$^{(***)}$	0.3025	0.7210$^{(***)}$	1.0397$^{(***)}$	−0.4417	0.5980$^{(***)}$
LnFDI	−0.0278	0.1363	0.1085	−0.0333$^{(*)}$	−0.1221	−0.1554$^{(**)}$
LnISA	−0.8314$^{(**)}$	0.1482	−0.6832	−3.1671$^{(***)}$	−1.2455	−4.4126$^{(***)}$
LnRDPE	0.4504$^{(***)}$	0.7858$^{(*)}$	1.2362$^{(***)}$	0.3571$^{(***)}$	0.152	0.5091$^{(***)}$
LnRDIE	0.3972$^{(***)}$	−0.3112	0.0860$^{(*)}$	0.4543$^{(***)}$	0.2298	0.6841$^{(***)}$
LnGDP	0.3037$^{(***)}$	−0.5234$^{(*)}$	−0.2198$^{(*)}$	0.4294$^{(***)}$	−0.4074	0.022$^{(***)}$

Notes. $^{(*),(**),(***)}$represent significance at 10%, and 5%, and 1% level respectively.

5.2. Policy suggestions

To fully play the role of financial system in promoting technological innovation, it is necessary to deepen the development of financial system so that it can better serve technological innovation. Measures should also be taken to adjust the structure of the financial system. It is also necessary to coordinate the optimal coupling between financial development and industrial development. Although the scale of financial assets in China is large, the efficiency of resource allocation of the financial system is not high, and the mismatch of structure and direction needs to be overcome. In the future, China is suggested to accelerate the improvement of financial market system and mechanism, encourage financial innovation, and provide diversified financial services for technological innovation.

China is suggested to introduce higher quality and higher efficiency foreign direct investment to spur domestic innovation. Eastern regions with high innovation level can use their scientific and technological advantages to attract the R&D of foreign enterprises to establish R&D institutions with foreign enterprises jointly, focus on innovation in high-tech industries, improve resource allocation capacity, and raise the original innovation level to a new level. The innovation path of the central and western regions should be transformed from imitating advanced technology to “learning by doing” to realize innovation and enhance regional innovation ability.

Further, the process of improving innovation capacity and the policy of strengthening independent innovation should be integrated into the upgrading of the secondary and tertiary industries. That is, innovation should be born in the process of industrial upgrading. On the one hand, industrial upgrading in most regions of China has great room to drive innovation. China should favor industries that are knowledge-intensive, have high comprehensive benefits and can lead the development direction of future industries, especially emerging industries represented by energy conservation and environmental protection, new energy and new materials. On the other hand, in order to drive the flow of regional human resources and the free entry and exit of capital, the government needs to transform from local protection to local opening and break down inter-regional urban barriers.

To summarize, innovation in China should be further facilitated to achieve an innovation-oriented economy. The key factor that drives, determines and undertakes innovation is people. Hence, only the quality and skills and motivation of humans are enhanced, can we have desired innovation. Otherwise, all will be in vain or just superficial. Further, the financial resources in China are fairly abundant, which intensifies the critical role of human capital. Hence, nowadays it is of crucial predominance to take all measures to enhance the quality and knowledge and skills of the whole labor force in China to achieve an innovation-driven growth. First, labor forces should be educated or recruited so that they can qualify for the high skill demanding jobs in capital- and technology-intensive firms in the advanced tertiary industry. When people are employed at more knowledge- or technology-intensive tertiary industry firms, they should be further educated and recruited so that they have the knowledge base to innovate. When the qualities of human capital are enhanced, firms’ absorptive abilities are also enhanced to the necessary level to benefit from FDI. Only when people are equipped with sufficient skills and knowledge, can they have the ability to migrate to where there are handsome-paying jobs and opportunities. Second, the paper suggests that China should distinguish and discriminate the development of different sub-sectors in the tertiary industry instead of developing the overall industry non-discriminatively. To be specific, those tertiary industry sub-sectors that are more labor-intensive and less innovative should be discouraged, while those that are more technology-intensive and more innovative should be encouraged. Particularly, real estate should be especially discouraged, including some financial institutions and activities, to alleviate the brain drain problem. Third, provinces that lag behind in innovation should issue better policies to attract intelligence, this, coupled with a well-educated and advance skill-equipped and thus mobile work force, can narrow provincial variations of in innovation.

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