Industrial structure upgrading and the impact of the capital market from 1998 to 2015: A spatial econometric analysis in Chinese regions

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HIGHLIGHTS

- We estimate the impact of capital markets on industrial structure upgrading (ISU) in China.
- We detect the presence of spatial autocorrelation of capital markets and ISU.
- We find the magnitude of spatial spillover effects in three sub-markets on ISU differ.
- We explore the impact of three sub-markets on ISU in four economic zones of China.
- We provide policy suggestions that better facilitate ISU.

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ABSTRACT

Using the theoretical framework of spatial econometrics, we estimate the impact of capital markets, i.e., stock markets, medium-and-long term bond markets, and medium-and-long term loan markets, on industrial structure upgrading (ISU) across 31 provinces in China from 1998 to 2015. We apply an explanatory spatial data analysis (ESDA) to detect the presence of spatial dependence and use a spatial Durbin model (SDM) to examine spatial distribution and spatial association. Although our overall estimation results from the 31 provinces indicate a degree of correlation between capital markets and industrial structure upgrading, the magnitude of spatial spillover effects in three sub-markets on ISU differ. We divide the 31 provinces into four economic zones, and explore the impact of three sub-markets on ISU in the eastern zone, central zone, western zone, and northeastern zone. Using our results, we provide policy suggestions that better facilitate ISU in China.

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1. Introduction

After 30 years of economic growth, beginning with the reform and opening up in 1978, China has become one of the most economically powerful countries in the world, and between 1978 and 2012 its average annual growth rate was 9.8% [1,2]. Recently, however, it has experienced a deceleration in economic growth. The average annual growth rate dropped from 7.7% in 2013 to 6.7% in 2016, and a strong downward pressure continues to persist [3]. To maintain a high economic

growth rate, an "industrial structure upgrading" (ISU) strategy has been proposed and implemented by the Chinese central government. ISU includes an adjustment in the composition of economic activity, and its primary task is to optimize resource allocation [4]. The capital market plays an important role in improving the efficiency of resource allocation across industries and regions [5] by facilitating the reallocation of capital resources from low value-added, poorly efficient, high energy consumptive industries to emerging high-tech industries, e.g., advanced manufacturing.

Because the industrial structure of the developed western economies reached maturity following the century-long adjustment after the First Industrial Revolution, the study of capital markets and ISU in developed economies has trailed off in recent decades, and most of the econometric research on this topic is 30 years old [6–10]. In recent years has there been an attempt to apply a similar approach to regions with less-developed economies [11–15], but most of the current literature uses traditional econometric models to study the interactions between capital markets, economic growth, and industrial upgrading. Because there has been little consideration of the distinctive characteristics of spatial data within regions and between regions, we must be cautious when interpreting the results. When there is spatial dependence, we must incorporate it into any of our econometric models [16].

In the early 1990s, Paul Krugman proposed New Economic Geography and received the 2008 Nobel Prize in Economic Sciences for this seminal contribution. In response to Krugman's work, economists have been integrating geographical data into all economic study, i.e., the geographical distribution of markets [17]. Various theories and models have thus been developed and studied, e.g., the core–periphery model [18], the urban system evolution model [19], the industrial concentration and trade model [20,21], and the technology innovation model [22–24]. Because most current results highlight interactions between agglomeration and growth processes, they may better explain regional growth [25]. Some studies consider spatial localization the key to understanding aspects of China's economy, and recent research has followed this path by using spatial econometrics to study proximity effects [26] and neighborhood effects [27], but there has been little study of how the spillover effects of capital markets affect ISU in Chinese regions. We thus carry out empirical research that uses spatial panel ISU models to study the capital market in China.

Since its 1978 reform and financial opening, China's rapid economic growth has been in (i) the industrial structure at provincial levels, within which there are strong regional disparities and a high spatial heterogeneity [28], and (ii) the capital market, which plays an ever-expanding role as China moves from central planning to an economic order [29]. This economic change suggests an important research question: what is the impact of the capital market on industrial structure upgrading? To answer this question we here provide an empirical analysis for understanding the spatiotemporal dynamics of the Chinese capital market and ISU. We apply an explanatory spatial data analysis (ESDA) to data from 31 Chinese provinces over the 1998–2015 period to empirically examine the spatial autocorrelation of the capital market and ISU. We utilize a spatial Durbin model (SDM) to reveal the spatial distribution and associated features. Taking into consideration the spatial dependence and heterogeneity of ISU at a provincial level, we examine the capital market and ISU to determine how spatial spillovers affect emerging economies. We organize our presentation as follows. Section 2 establishes econometric models and describes the estimation methods. Section 3 addresses variable selection and data collection. Section 4 analyzes the empirical results. A further analysis of the four major economic zones in China is described in Section 5. Section 6 presents some concluding remarks and policy implications.

2. Methodology

The examination of spatial data is strongly affected by the location from which observations are made. Neighboring regions affect each another and proximate locations often share more similarities than widely-spaced locations [30]. In this section, we examine two types of ESDA and four types of spatial econometric models.

2.1. Explanatory spatial data analysis

Before applying spatial econometric models, we must present the level of spatial dependence. We use ESDA to detect whether the capital market (or industrial structure) of one province is influencing the development of a neighboring capital market (or industrial structure). We use (i) the global Moran I and (ii) the local Moran scatterplot to detect the spatial autocorrelation of the capital market and the industrial structure.

(1) The global Moran I

The global Moran I quantifies the similarity of observations among adjacent geographical units from a global perspective and is used to analyze the overall spatial autocorrelation degree and spatial distribution pattern. The global Moran I is defined

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

where $\bar{x} = 1/n \sum_{i=1}^{n} x_i$, $S^2 = 1/n \sum_{i=1}^{n}(x_i - \bar{x})^2$, x_i is the observed value in location i, $\bar{x}$ is the mean of the observed value across all locations, and w_{ij} is an element value in the binary spatial weight matrix that describes the spatial relationship between location i and location j. We here apply one of the most frequently used spatial contiguity based weight matrices [31]: when two provinces share a geographical border $w_{ij} = 1$, otherwise $w_{ij} = 0$.

The global Moran I ranges from -1 to 1 due to the use of the standardized spatial weight matrix. When $I > 0$, the capital market (or industrial structure) has a positive correlation, which indicates that they tend to be clustered in space. Similarly, when $I < 0$, the province tends to be surrounded by neighboring provinces with dissimilar values. When $I = 0$, the spatial pattern of the capital market (or industrial structure) is random.

(2) Local Moran scatterplot

Global spatial autocorrelation statistics assume spatial stationarity, and that the observation values and variances at all locations are constant. Spatial processes are likely to be unstable, especially when the amount of data is very large, which makes the spatial stability assumption unrealistic [32]. Local spatial autocorrelation statistics can be used to identify different spatial patterns (or spatial aggregation patterns) that may exist in different spatial locations. This allows us to observe local non-stationarity in different spatial locations and to find spatial heterogeneity among the data [33]. A local Moran scatterplot is developed in ESDA. In our study, the Moran scatterplot is a two-dimensional scatterplot Wz versus z in which each point represents a province, where $z_i = (x_i - \bar{x}) / \sum_{i=1}^{n} (x_i - \bar{x})^2$, $\sum_{i}^{n} \sum_{j \neq i}^{n} w_{ij} = n$. This scatterplot is centered on 0 and is divided into four quadrants that represent different types of spatial association. The first quadrant is the high–high (HH) cluster quadrant, i.e., provinces with high-performing capital markets (or industrial structures) surrounded by provinces with high-performing capital markets. Similarly, the second, third and fourth quadrants are the low–high (LH), low–low (LL) and high–low (HL) cluster quadrants, respectively.

2.2. Spatial econometric models

Spatial econometrics experts have proposed a variety of models to explore different spatial interaction effects. Among them, the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM) are widely used. Which model is selected is determined by whether the dependent or independent variables have spatial interaction effects.

(1) Basic form of the spatial panel model

The SLM is applied when there is an endogenous interaction among the dependent variables and is more appropriate when the goal is to determine the existence and quantify the strength of spatial interaction. The specification of the spatial lag model is

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \boldsymbol{x_{it}} \boldsymbol{\beta} + \mu_i + \xi_t + \varepsilon_{it}, \tag{2}$$

where i is an index for the cross-sectional dimension (spatial units), with $i = 1, \ldots, N$, and t is an index for the time dimension (time periods), with $t = 1, \ldots, T$. y_{it} denotes the dependent variable, $\sum_{j=1}^{N} w_{ij} y_{jt}$ denotes the endogenous interaction effects among the dependent variable, i.e. the spatial lag term of dependent variable, w_{ij} is an element of the $N \times N$ matrix describing the spatial configuration or arrangement of the units, $\boldsymbol{x_{it}}$ denote the K-dimensional independent variables, $\boldsymbol{\beta}$ represent the parameters to be estimated of independent variables, δ is the spatial autoregressive coefficient, μ_i denotes spatial specific effect, ξ_t denotes time specific effect, and ε_{it} is a disturbance term.

The SEM is used when the spatial dependence works through omitted variables. It uses an error process utilizing errors from different regions displaying spatial covariance. The model is

$$y_{it} = \boldsymbol{x_{it}} \boldsymbol{\beta} + \mu_i + \xi_t + u_{it},$$
$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it}, \tag{3}$$

where $\sum_{j=1}^{N} w_{ij} u_{it}$ denotes the interaction effects among the disturbance terms of the different units, λ describes the spatial autocorrelation coefficient for the error lag, and the remaining symbols are the same as in the previous equation.

The SDM captures both endogenous and exogenous spatial interactions, where both the spatial lag term of the dependent variable and the spatial lag term of independent variable affect the dependent variable. The model is expressed

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \boldsymbol{x_{it}} \boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij} \boldsymbol{x_{jt}} \boldsymbol{\theta} + \mu_i + \xi_t + \varepsilon_{it}, \tag{4}$$

where $\sum_{j=1}^{N} w_{ij} \boldsymbol{x_{jt}}$ denotes the exogenous interaction effects among the independent variables, i.e., the spatial lag terms of independent variables. The $\boldsymbol{\theta}$, just as $\boldsymbol{\beta}$, represent fixed and unknown parameters to be estimated.

(2) Estimation and selection of spatial panel model

Spatial econometric models are estimated using maximum likelihood (ML) methods, and the Lagrange multiplier (LM) and the log-likelihood (Log-L) tests are used to test the presence of the two possible forms of autocorrelations: LM-SLM for an autoregressive spatial lag variable and LM-SEM for a spatial autocorrelation of errors. To determine which specification is more appropriate, we use a decision rule proposed by Ref. [34]. We first select SDM, and then we use the estimated model parameters to test the null hypotheses $H_0: \theta = 0$ and $H_0: \theta + \delta\beta = 0$. According to the results, we determine whether the SDM can be simplified to a SLM or SEM. The commonly used test methods are the likelihood ratio (LR) test and the Wald test.

Table 1
The variable type, variable name, symbol and definition.

Variable type	Variable name	Symbol	Definition
Explained variables	Degree of ISU	IS	$\sum_{i=1}^{n} K_i \sqrt{P_i/L_i} \quad n = 1, 2, \ldots, n$
Explanatory variables	Stock market development level	STOCK	Financing amount per capita per province over China's average financing amount per capita in the stock market.
	Loan market development level	LOAN	Financing amount per capita per province over China's average financing amount per capita in the loan market.
	Bond market development level	BOND	Financing amount per capita per province over China's average financing amount per capita in the bond market.
Control variables	Consumption demand	ICD	Ratio of individual consumption per province to China's average individual consumption.
		GCD	Ratio of government consumption per province to China's average government consumption.
	Human capital level	EDU	Ratio of average years of schooling per province to China's average years of schooling.
	Technological progress	TECH	Ratio of R&D investment per capita per province to China's average R&D investment per capita.
	Foreign direct investment	FDI	Ratio of FDI per capita per province to China's average FDI per capita.

3. Variable selection and data collection

3.1. Variable selection and description

Industrial structure upgrading. Most of the existing ISU measurement literature uses the ratio of the secondary and tertiary industrial added value to gross domestic product (GDP) [35–37], but ISU levels are also affected by improvements in labor quality and labor productivity in each industry. Ref. [38] defines the measurement of ISU to be

$$IS = \sum_{i=1}^{n} K_i \sqrt{P_i/L_i} \quad n = 1, 2, \ldots, n, \tag{5}$$

where *IS* is the level of industrial structure upgrading, K_i is the proportion of the product of industrial sector *i* in all industrial sector products, P_i is the product of the industrial sector *i*, L_i is the employment in industrial sector *i*, and P_i/L_i is the labor productivity of industrial sector *i*. We here set the number of industrial sectors *n* to 3 to reflect the primary, secondary and tertiary industries in the national economy.

Capital market. According to the definition in Ref. [39], the capital market is divided into three sub-markets, i.e., the stock market, the medium-and-long term loan market, and the medium-and-long term bond market. We apply per capita indicators to eliminate regional-scale differences among the provinces, and use the financing amount per capita for each province over China's average financing amount per capita in the stock market, loan market, and bond market to measure the degree of capital market development.

We also select several control variables to ensure the stability of the estimated results.

(1) Consumption demand. The multi-level consumption structure forces manufacturers to constantly improve their procedures, design new products, and accelerate their multi-level industrial structure upgrading. The consumption demand includes both individual and public consumption. Here we use the ratio between the individual consumption per province and China's average individual consumption demand (ICD) to measure the individual consumption in each province. Similarly, we use the ratio between government consumption per province and China's average government consumption demand (GCD) to measure the public consumption in each province. (2) Human capital level. This indicator measures the knowledge level and management skill of workers, which strongly affect ISU. We thus use the ratio between the average years of schooling per province and China's average years of schooling (EDU) to measure the level of human capital. (3) Technological progress. This is the strongest factor promoting the ISU and can transform the production mode, change the organizational and management mode, and promote the evolution of the industrial structure to an advanced level. We use the ratio between R&D investment per capita per province and China's average R&D investment per capita (TECH) to measure the technological progress in each province. (4) Foreign direct investment (FDI). FDI brings advanced technology and management knowledge from developed economies and creates a "technological spillover" that affects the industrial structure. We use the ratio between FDI per capita per province and China's average FDI per capita (denoted as FDI) to measure the FDI level of each province. The variable and its definitions are provided in Table 1.

3.2. Data collection

Our sample includes 31 provinces, province-level municipalities, and ethnic minority autonomous regions in China over the 1998–2015 period, as shown in Fig. 1. For convenience, in this study we refer to all of them as provinces. Because of

Fig. 1. Province map in China. Note: China has 34 provincial-level administrative units, consisting of 23 provinces, 4 municipalities (Beijing, Tianjin, Shanghai, and Chongqing), 5 autonomous regions (Guangxi, Inner Mongolia, Tibet, Ningxia, and Xinjiang) and 2 special administrative regions (Hong Kong and Macau). In the bottom right corner, South China Sea is shown in rectangle box.

missing data, we do not include Hong Kong, Macao, and Taiwan in our sample. The bond-market trading system in China was established from 1998 to 2003, and then experienced rapid development [38]. The most important events in this period were the inception of the interbank market in 1997, the issue of corporate bonds in 2007, the issue of medium-term notes in 2008, and the issue of local government bonds in 2009. To ensure stability and completeness, we used data from the period 2007–2015 for the medium- and long-term bond market.

We obtained data on the value-added levels in the secondary and tertiary industries and on the GDP between 1998 and 2015 from the China Center for Economic Research (CCER). We obtained stock market data between 1998 and 2015 for each province from the *China Securities and Futures Statistical Yearbook (2000–2016)*. We obtained data on corporate bonds and local government bonds for each province between 2007 and 2011 and data on medium-term notes between 2009 and 2010 from the website http://www.chinabond.com.cn/. We obtained data on all other types of bonds between 2011 and 2015, except government bonds, from the *China Securities Futures Statistical Yearbook (2012–2016)*. We obtained data on medium-and-long term loan markets between 1998 and 2015 for each province from the *China Financial Statistical Yearbook (1998–2016)*. We obtained data on consumption per province and R&D investment per capita from the China Stock Market & Accounting Research (CSMAR) database. We obtained data on the average years of schooling per province and data on FDI from the *China Statistical Yearbook (2008–2016)* and the *Statistical Yearbook* of each province.

4. Empirical results and discussion

4.1. Spatial autocorrelation measures

(1) Global Moran *I* analysis

Using the data from 31 provinces in China from 1998 to 2015, we calculate the global Moran *I* of the industrial structure upgrading level (IS), stock market level (STOCK), bond market level (BOND), and loan market level (LOAN) to test the global spatial autocorrelation of the explanatory variables variable (capital market) and the explained variable (ISU). The results are summarized in Table 2.

The results of the global Moran *I* test of industrial structure for most years are statistically significant and have a *p*-value smaller than 0.05. We also find that the spatial dependency of the industrial structure in each province tends to decrease year

Table 2
Global Moran *I* test for provincial capital market and ISU in China.

Year	IS	p	STOCK	p	BOND	p	LOAN	p
1998	0.2496	0.0088	0.0483	0.4497	–	–	0.1078	0.1915
1999	0.2466	0.0096	0.0848	0.2739	–	–	0.1162	0.1663
2000	0.2322	0.0140	0.0261	0.5822	–	–	0.0733	0.3234
2001	0.2260	0.0164	0.0548	0.4144	–	–	0.0868	0.2662
2002	0.2271	0.0159	−0.0260	0.9461	–	–	0.0742	0.3193
2003	0.2362	0.0126	0.0239	0.5960	–	–	0.1025	0.2084
2004	0.2343	0.0132	0.0553	0.4117	–	–	0.1092	0.1869
2005	0.2432	0.0105	0.0136	0.6636	–	–	0.1347	0.1199
2006	0.2414	0.0110	0.0124	0.6723	–	–	0.1339	0.1216
2007	0.2406	0.0112	0.0532	0.4228	−0.0005	0.7609	0.1488	0.0917
2008	0.2372	0.0122	0.0400	0.4975	0.0150	0.6544	0.1504	0.0890
2009	0.2112	0.0236	0.0017	0.7456	0.0016	0.7461	0.1682	0.0620
2010	0.2151	0.0214	0.0294	0.5615	0.0574	0.4010	0.1700	0.0598
2011	0.2572	0.0071	−0.0094	0.8245	0.0182	0.6333	0.1689	0.0611
2012	0.2242	0.0171	0.0340	0.5332	0.0234	0.5992	0.1669	0.0638
2013	0.1784	0.0499	0.0121	0.6741	0.0694	0.3416	0.1675	0.0630
2014	0.1402	0.1082	0.0342	0.5317	0.0705	0.3362	0.1697	0.0602
2015	0.1094	0.1864	0.0999	0.2174	0.0586	0.3944	0.1749	0.0538

Note: *p* denotes *p*-value. "–" indicates that no data are available. The bond market in China is still in the infant stage and the data for several classes of bonds are missing in the statistical database before 2007. In order to ensure the stability and completeness of data, the sample period of the bond market was selected from 2007 to 2015.

by year, because the Moran *I* value decreases from 0.2496 in 1998 to 0.1094 in 2015. The industrial structure in all provinces of China shows a strong positive spatial correlation, which indicates that their interdependence with the industrial structure of neighboring provinces, that an industrial structure upgrade in one province will have a positive spatial spillover effect on the industrial upgrades in neighboring provinces.

The spatial dependence of the capital market across provinces is not clear. In three sub-markets, only the loan market exhibits a positive and rising global Moran *I*, which is relatively significant compared to the two other sub-markets. The loan market passes statistical hypothesis testing at the 10% significance level from 2007 to 2015, and the Moran *I* value increases from 0.1488 in 2007 to 0.1749 in 2015. For the stock and bond markets, the global statistical test results are not significant, indicating that in different provinces there is little spatial correlation between them. This reflects the relative immaturity of China's capital market, and the fact that it is still governed by an administrative mechanism [40].

(2) Local Moran scatterplot analysis

To further study the provincial spatial correlation of industrial structure and the capital market in China, we show the Moran scatterplot for IS, STOCK, BOND, LOAN, in Figs. 2 and 3. The detailed results of 31 provinces in four quadrants are presented in Table S1 of supplemental document.

Fig. 2 shows the positive spatial correlation among all the provincial industrial structures of China and how the industrial structures among neighboring provinces is highly correlative and mutually promotes industrial structure upgrading. In addition, the scatterplot in 2015 is more dispersed than in 1998, and the outliers are more conspicuous in the second and the fourth quadrants, which indicates that the positive spatial correlation of ISU in the provinces is becoming weaker.

Fig. 2 also shows dynamic changes in industrial structures. For example, Fujian moved from the high–high quadrant to the low–low quadrant due to a siphoning by two developed neighboring provinces, e.g., Zhejiang and Guangdong. Because Zhejiang and Guangdong are among biggest provincial economies in China, they siphon scarce financial, labor, and investment resources from Fujian. In northeast China, Jilin moved from the low–high quadrant to the high–high quadrant, and Heilongjiang moved from the high–low quadrant to the high–high quadrant, and then to the low–high quadrant. Because in 2013–2015 the provincial governments in Heilongjiang, Jilin, and Liaoning admitted providing fake data to the National Bureau of Statistics, the IS performance data from these provinces may not reflect the real situations. Note that the performance of the industrial structure of Shandong dropped from the high–high quadrant in 2011–2013 but returned after 2014. This occurred because its economic structure was dominated by state-owned enterprises with a high energy consumption and high pollution levels, but more recently these state-owned enterprises have switched their focus from attaining the highest GDP irrespective of rational industrial structure to one that takes into account sustainable growth and the control of pollution. What is occurring in Shandong is that it is reforming the state-owned enterprises and promoting the development of a private economy, which ultimately changes its industrial structure. In contrast with Shandong province, Jiangsu and Zhejiang already have many private corporations that are "sources of vitality" that keep them in the high–high quadrant.

China has three major economic circles, the Yangtze River Delta (encompassing Shanghai, Jiangsu, and Zhejiang), Pearl River Delta (encompassing Hong Kong, Macao, and Guangdong) and the Beijing–Tianjin–Hebei metropolitan region (also known as the Jing–jin–ji economic circle). Because Hong Kong and Macao are not included in our sample, we do not analyze the Pearl River Delta economic circle. Fig. 2 shows that in the Yangtze River Delta economic circle there are positive spatial
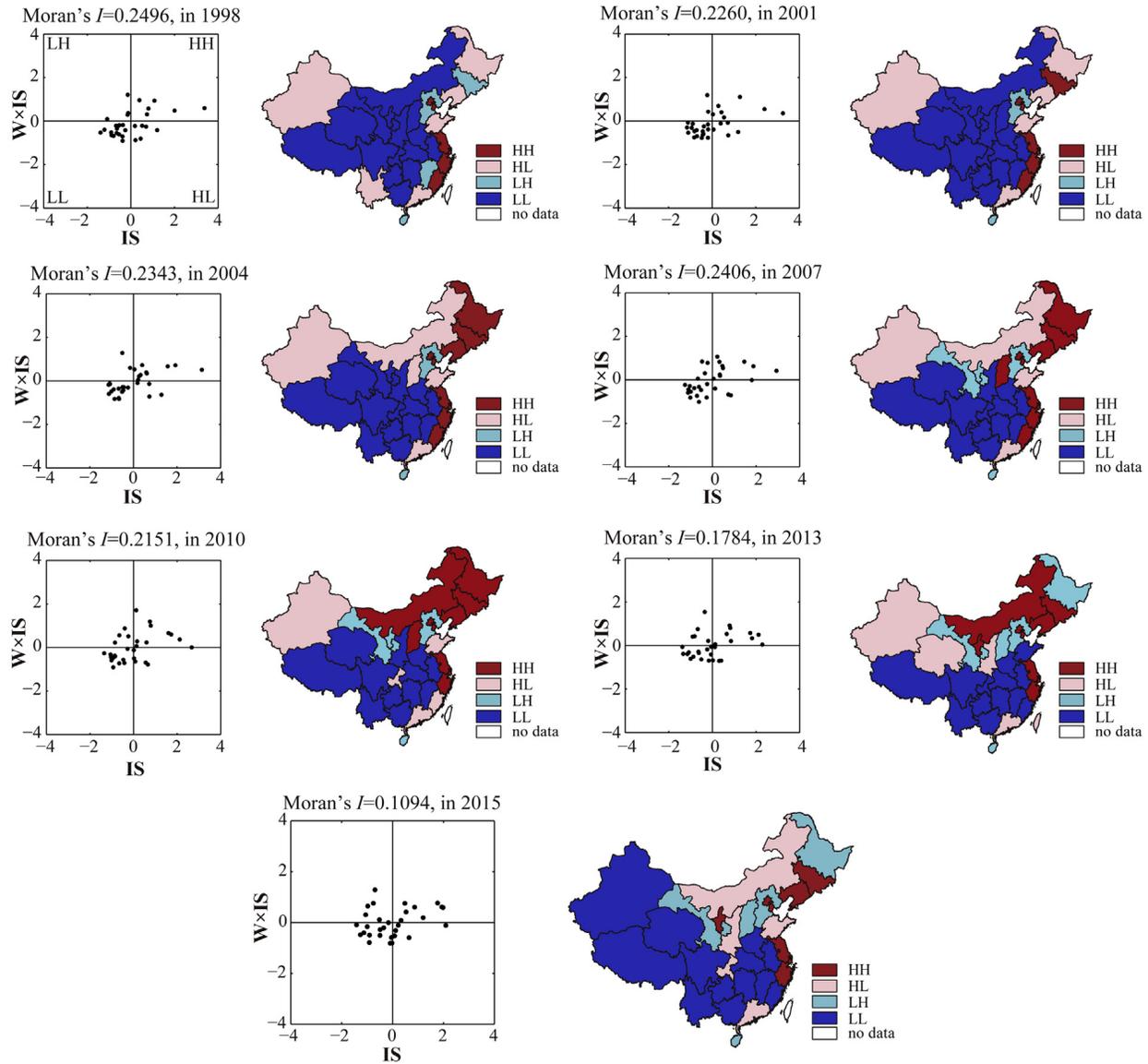
Fig. 2. Local Moran scatterplot analysis of industrial structure, from 1998 to 2015.

dependencies in the industrial structure, which means the industries in the three provinces have developed side by side through mutual cross-fertilization. On the contrary, there are negative spatial dependencies in the industrial structure in the Beijing–Tianjin–Hebei economic circle. Beijing and Tianjin siphon away resources from Hebei. Fig. 2 also indicates that in 1998 the industrial structure of the majority of provinces in the central and western regions of China were low-performing. With the economic growth of the last decade, the coastland regions transferred industries to the central regions and promoted its industrial upgrading, but this industry transfer did not benefit western regions.

Fig. 3 shows a local spatial correlation in the development of China's capital market. The local Moran scatterplot of the stock market and bond market shows a polarization, which could explain why the global spatial correlation test of these two sub-markets is insignificant (as shown in Table 2). The high development level of the sub-markets in Beijing, Shanghai and Guangdong causes the remaining provinces to fall into the third quadrant (low–low autocorrelation pattern) and to have a lower development level [41]. Although there are many provinces in the third quadrant, the spatial correlation is very weak, and the global spatial correlation is insignificant. From a vertical perspective, in contrast to 1998 the spatial correlation of the loan market in 2015 is stronger, and due to spatial spillover an increasing number of provinces have moved out of the third quadrant.
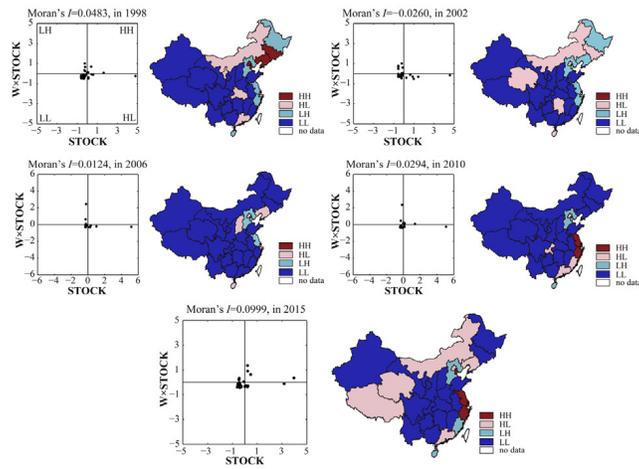
(a) Moran scatterplot and map of stock market, from 1998 to 2015.
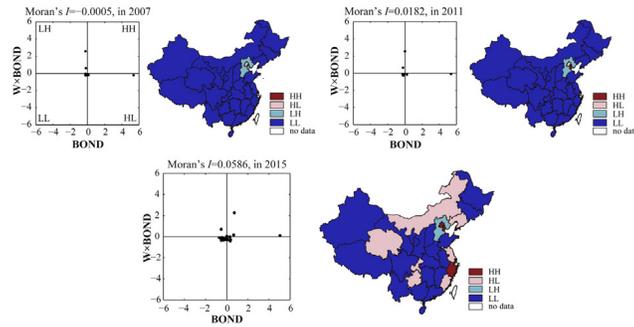
(b) Moran scatterplot and map of bond market, from 2007 to 2015.
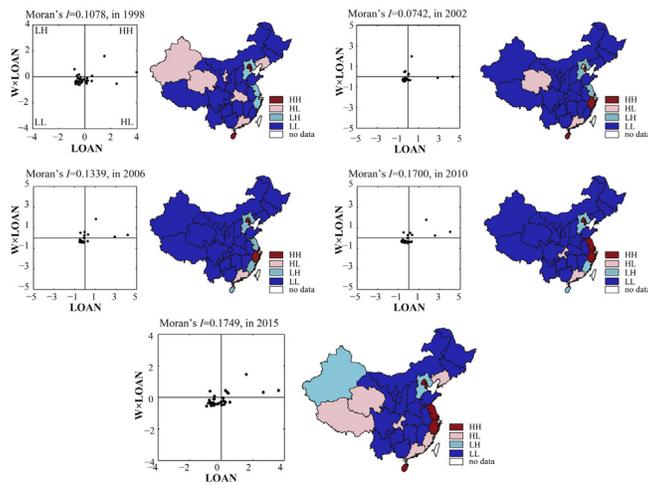
(c) Moran scatterplot and map of loan market, from 1998 to 2015.

Fig. 3. Local Moran scatterplot analysis.

Table 3
The summary of Wald test and LR test.

Test	Statistics	p
Wald test for spatial lag	7.6556	0.0537
LR test for spatial lag	6.3172	0.0972
Wald test for spatial error	7.5805	0.0555
LR test for spatial error	7.4798	0.0581

Note: p denotes p-value.

4.2. Spatial panel model specifications

Using the spatial autocorrelation analysis in Section 4.1, we find that all dependent variables and independent variables have a certain degree of spatial autocorrelation, which indicates that the spatial econometric model can be used to investigate the relationship between the capital market and ISU. After introducing the spatial lag terms of the capital market and ISU, we present a spatial panel model

$$
\begin{aligned}
is_{it} = {} & \delta \sum_{j=1}^{N} w_{ij} is_{jt} + \beta_1 stock_{it} + \theta_1 \sum_{j=1}^{N} w_{ij} stock_{jt} + \beta_2 bond_{it} + \theta_2 \sum_{j=1}^{N} w_{ij} bond_{jt} \\
& + \beta_3 loan_{it} + \theta_3 \sum_{j=1}^{N} w_{ij} loan_{jt} + \boldsymbol{\beta_4 x_{it}} + \mu_i + \xi_t + \varepsilon_{it},
\end{aligned}
\tag{6}
$$

where $\sum_{j=1}^{N} w_{ij} stock_{jt}$, $\sum_{j=1}^{N} w_{ij} bond_{jt}$ and $\sum_{j=1}^{N} w_{ij} loan_{jt}$ are the spatial lag terms of the independent variables, respectively. $\sum_{j=1}^{N} w_{ij} is_{jt}$ is the dependent variable's spatial lag term. $\boldsymbol{x_{it}}$ is a set of control variables, μ_i is the spatial fixed effect, ξ_t is the time fixed effect, ε_{it} is the error term, and our study assumes that μ_i, ξ_t, and ε_{it} are independent and identically distributed. δ is the spatial autoregressive coefficient λ is the spatial autocorrelation coefficient, and β and θ are the parameters to be estimated.

4.3. Spatial panel model selection, estimation and analysis

We follow the guidelines proposed in Ref. [34], and preliminarily use the SDM to quantify the impact of the capital market on ISU. Then we test the null hypotheses $H_0: \theta = 0$ and $H_0: \theta + \delta\beta = 0$ to determine whether the SDM can be simplified to the SLM or SEM. Table 3 shows that both the Wald test and LR test reject the null hypothesis that the SDM can be simplified to be SLM or SEM at a significance level of 10%. Thus the SDM is a more appropriate model for exploring the spatial relationship between the capital market and ISU.

We use the spatial panel data from 2007 to 2015 and a maximum likelihood (ML) approach to estimate the SDM of the capital market and industrial structure upgrading. Table 4 shows the estimation results of the ordinary least square (OLS), SLM, and SEM panel models.

Table 4 shows estimation results indicating that the SDM has the highest goodness of fit ($R^2 = 0.9651$) and the biggest log-likelihood value (515.6651), when compared with OLS, SLM, and SEM. The SDM model is thus better able to capture the spatial dependence. This is consistent with the statistical test results in Table 3. We will thus use the SDM estimation results in the following analysis.

(1) The independent variables (STOCK, BOND, and LOAN) indicate that the effects of the three sub-markets on ISU differ. Indirect financing channels, i.e., loan markets, have a positive impact on ISU with an estimated coefficient of 0.05022 ($p = 0.01537$). Direct financing channels, i.e., the stock and bond markets, have a weak and negative effect on ISU. The estimated coefficients of the spatial lag term in the stock and bond markets (W × STOCK and W × BOND) are not significant, indicating that there is no spatial dependence in the development of China's stock and bond markets. The estimated coefficients of the spatial lag term in the loan market (W × LOAN) are statistically significant, indicating that the loan market at the provincial level has spatial spillover effects, which is consistent with test results for the capital market spatial autocorrelation in Section 4.1. The negative W × LOAN indicates that the loan market strangles ISU in neighboring provinces. Thus direct financing channels in China (stock and bond markets) are not sufficiently mature, but that indirect financing channels (loan market) are mature. This is consistent with the results of previous studies [42,43].

(2) The spatial lag term for the industrial structure upgrading degree (W × IS) is statistically significant, with an estimated coefficient 0.38177, which is consistent with test results in Section 4.1 and also confirms the validity of using the lag term for the dependent variable in our spatial panel model. In addition, the spatial spillover effect of ISU shows a positive impact.

(3) The control variables of individual consumption demand (ICD), government consumption demand (GCD), human capital level (EDU), and technological progress (TECH) are all statistically significant, positive determinants. As expected, the coefficients of foreign direct investment (FDI) are positive but not statistically significant. Note that consumption demand is the strongest factor in China's ISU and strongly affects the advancement of industrial structure. The sum of the estimated coefficients for individual and governmental consumption demand is 0.23, and the enhancement of individual consumption demand is more obvious (with an estimated coefficient of 0.14150), indicating that China tends toward a domestic consumption-driven growth path [44]. In 2017 domestic consumption accounted for 58.8% of China's economic

Table 4
The estimation results of the spatial panel model of provincial capital market and industrial structure in China.

Variable	OLS	SLM	SEM	SDM
STOCK	−0.00242* (0.09804)	−0.00229 (0.12852)	−0.00206 (0.16990)	−0.00226 (0.12736)
BOND	−0.00631*** (0.00016)	−0.00627*** (0.00024)	−0.00652*** (0.00010)	−0.00668*** (0.00010)
LOAN	0.02255 (0.22020)	0.02528 (0.18400)	0.03851* (0.05490)	0.05022** (0.01537)
ICD	0.14449*** (0.00170)	0.15759*** (0.00082)	0.14695*** (0.00115)	0.14150*** (0.00255)
GCD	0.09982*** (0.00004)	0.08202*** (0.00086)	0.07933*** (0.00163)	0.08172*** (0.00087)
EDU	0.15470* (0.06027)	0.12785 (0.13133)	0.12501 (0.14411)	0.14449* (0.08989)
R&D	0.06187*** (0.00198)	0.05568*** (0.00649)	0.04956** (0.01643)	0.04497** (0.02819)
FDI	0.01012* (0.09966)	0.00983 (0.12036)	0.00871 (0.18255)	0.00661 (0.39791)
W × IS	–	0.28640*** (0.00002)	–	0.38177*** (0.00000)
W × STOCK	–	–	–	−0.00137 (0.66012)
W × LOAN	–	–	–	−0.06780** (0.01762)
W × BOND	–	–	–	0.00357 (0.33125)
W × u	–	–	0.39294*** (0.00000)	–
R²	0.9617	0.9638	0.9615	0.9651
Log-L	507.3190	512.5065	511.9252	515.6651

Notes: The *p*-values are given in the parentheses. "–" symbols denote that the corresponding spatial panel model does not produce the value for this variable.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

growth, and net exports contributed only 9.1% of GDP growth. The human capital level (EDU) played a significant positive role in promoting the ISU with estimated coefficient 0.14449, which is consistent with previous findings in Ref. [45] and indicates that the level of human capital in China can be matched by the ISU. Human capital utilizes material, equipment, and technology through its elemental and efficiency functions. Technological progress (TECH) plays a positive role in promoting China's ISU in line with previous findings in Ref. [46] that technological innovation can endogenously drive economic growth and directly improve labor productivity, and also promote regional ISU. Foreign direct investment (FDI) has a positive effect on ISU, but its impact is relatively weak, indicating that FDI has not contributed to the growth of high-tech enterprises in China. China's ISU is instead more strongly promoted by endogenous technological innovation.

5. Further analysis and discussion

Because we have seen that the capital market has a spatial effect on the ISU at the provincial level, to further explore this effect we group the 31 provinces into four major economic zones: the eastern, central, western, and northeastern. Fig. 4 shows this spatial grouping. Table 5 shows a summary of the estimated spatial effects of these four economic zones and the impact of the capital market in each group on ISU.

The results of the capital market in these four economic zones present that: (1) The stock market (STOCK) promotes ISU in the eastern and central zones, but hinders it in the northeastern zone (note the negative STOCK values in Table 5). (2) The loan market (LOAN) strongly affects ISU in the central zone, with an estimated coefficient of 0.7029. This is consistent with Ref. [37], which examines the relationship between bank size and industrial upgrading in the central zone. Zhang [47] finds that the central zone has a bank-dominant financing structure, which means the bank loan is the major driver for ISU. (3) Policy guidance in the northeast zone causes the bond market to strongly promote ISU, with an estimated coefficient 0.1482. In recent years the Chinese government has implemented a revitalization of the old industrial bases in the northeastern zone, which enables it to issue new kinds of corporate bonds and expand the scope of bond financing. These policies have enabled the bond market in the northeastern zone to provide a financing channel for new and expanding enterprises.

The spatial lag terms in the four major economic zones show that: (1) Because there is only a handful of listed companies in the northeastern zone, this poor economic state causes the development of the stock market in one province to inhibit ISU in neighboring provinces of the zone through a siphoning effect. (2) In the central zone the spatial spillover effect of the
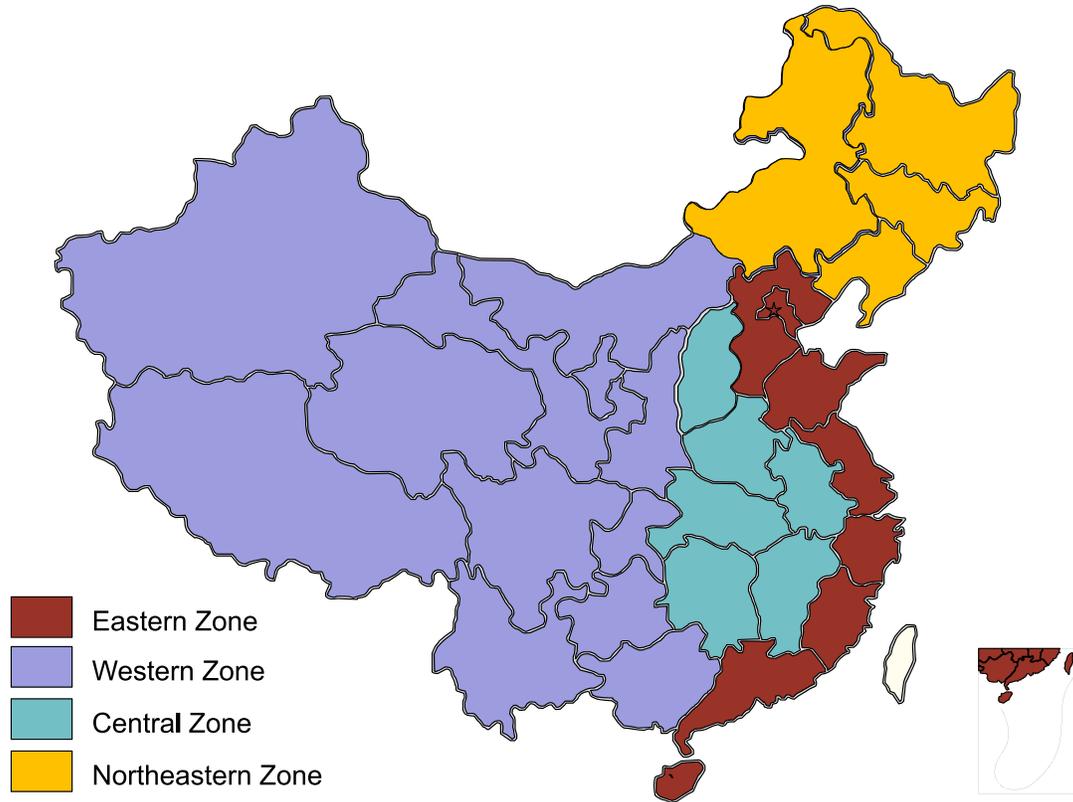
Fig. 4. The geographic location of China's four major economic zones.

loan market on ISU is positive, indicating a good interaction between the loan markets and ISU in neighboring provinces. In contrast, the development of isolated loan markets in the interior provinces of the western zone impedes ISU in neighboring provinces. (3) The spatial spillover effect of the bond market on industrial structure upgrading is positive in the northeastern zone, but insignificant in the other three zones.

With the exception of the central zone, the positive spatial spillover effect of ISU is statistically significant, but negative for the 31 provincial estimated results in Section 4.3, which shows that ISU between the neighboring provinces in each region (eastern, western and northeastern economic zones) is mutually hindering due to the industrial structure convergence within each economic zone. This generates a "Prisoners Dilemma" competition among provinces for limited resources and market share. Studies of the convergence of industrial structure in China find that the inhibitory effect is primarily in technology-intensive industries in the eastern zone and in labor-intensive industries in the western and northwestern zones [48,49].

The control variable estimations indicate that individual consumption demand (ICD) positively affects industrial structure upgrading in the eastern zone and negatively correlates in the northeastern zone. In contrast, government consumption demand (GCD) positively affects industrial structure upgrading in the northeastern and western zones, indicating that ISU in these two zones depends on government support. The government strongly affects the economy and lacks vitality. The level of human capital (EDU) positively correlates with ISU in the eastern zone, but negatively correlates with ISU in the northeastern zone. Technological progress (R&D) positively correlates with ISU in eastern and central zones, but negatively correlates with ISU in the northeastern zone. Foreign direct investment (FDI) has a weakly positive effect in the eastern zone, but a strongly negative effect in the central and northeastern zones. This is the case because eastern zones have a geographical advantage that enables its provinces to attract more foreign investment.

6. Conclusions and policy implications

Guiding capital markets so that they support industrial structure upgrading (ISU) and economic growth is both an academic and practical concern. We have defined the capital market to be stock markets, medium-and-long term bond markets, and medium-and-long-term loan markets, and examined their impact on ISU in China from 1998 to 2015. We investigate and analyze possible spatial autocorrelations between the capital market and industrial structures at the provincial level across 31 Chinese provinces. We then construct a spatial econometric model to explore the relationship between the capital market and ISU. We divide the 31 provinces into four major economic zones and further study the spatial

Table 5
The estimation results of the spatial panel model of China's four major economic zones.

Variables	Eastern	Central	Western	Northeastern
STOCK	0.00401**	0.02908**	−0.00089	−0.14664***
	(0.01955)	(0.02061)	(0.66067)	(0.00000)
LOAN	0.02360	0.70289***	−0.02052	0.14820**
	(0.15073)	(0.00000)	(0.67768)	(0.03625)
BOND	−0.00364***	−0.00219	0.02131	0.18541***
	(0.00141)	(0.88607)	(0.22659)	(0.00072)
ICD	0.14402***	0.05996	−0.18617	−0.35815***
	(0.00008)	(0.65421)	(0.16508)	(0.00262)
GCD	0.02575	−0.07574	0.11365***	0.14826**
	(0.34360)	(0.29985)	(0.00359)	(0.02452)
EDU	0.41310***	−0.17141	−0.04759	−0.65805**
	(0.00294)	(0.46471)	(0.73970)	(0.02354)
R&D	0.03895**	0.49584***	−0.10745	−0.12574**
	(0.02532)	(0.00000)	(0.39436)	(0.04158)
FDI	0.01262*	−0.23012***	0.02594	−0.02361*
	(0.08431)	(0.00000)	(0.25290)	(0.09862)
W × STOCK	−0.00384	0.05432**	−0.00167	−0.25828***
	(0.15259)	(0.01017)	(0.71056)	(0.00001)
W × LOAN	−0.01343	1.37538***	−0.33556***	0.48337
	(0.49110)	(0.00000)	(0.00005)	(0.18536)
W × BOND	0.00348	−0.02030	−0.01637	0.27117**
	(0.13408)	(0.61515)	(0.59689)	(0.03486)
W × IS	−0.28795***	0.19065	−0.27304**	−0.62005***
	(0.00296)	(0.12382)	(0.03908)	(0.00029)
R^2	0.9899	0.9751	0.9592	0.9911
Log-L	223.5148	148.1414	198.6307	91.6241

Notes: The p-values are given in the parentheses.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

effect of the capital market on ISU. Using our results in Sections 4 and 5, we offer three policy suggestions for optimizing the industrial structure upgrading in China.

First, local governments in the western economic zone should seize the opportunities of One Belt One Road (OBOR) initiative, and benefit from upgrades in infrastructure, utilities, energy and related industries. Over the last decade the eastern zone upgraded their industries and transferred backward industries to the central zone, but the western zone missed this opportunity. The Chinese OBOR initiative, launched in 2013, will link China's western zone and Europe. Xinjiang will become a financial hub in the western economic zone, and western regions, such as Chongqing, Shaanxi, Sichuan, Xinjiang and Yunnan, will focus on infrastructural upgrades, urbanization projects, and expanding international trade opportunities. Some underdeveloped western provinces with rich natural and agricultural resources, such as Gansu, Ningxia and Xinjiang, will upgrade their technology and improve productivity and efficiency.

Second, China must accelerate the reform of its traditional financial sectors. Estimations at both the overall and economic zone levels indicate that the capital market's contribution to ISU is weak, and that its capital utilization is inefficient. China's current financing is still predominantly indirect. China's repressive financial policies make loan markets the main channel for promoting ISU, and funds raised by the stock and bond markets fail to boost industrial restructuring and upgrading. Because these two sub-markets are strongly speculative and unable to facilitate direct financing, China must reform its traditional financial sectors and promote a smoothly functioning legal system, so that the capital market can better facilitate regional ISU.

Finally, local governments must choose to either catch up or be complementary. Because there is a positive spatial dependence of ISU amongst zones, authorities should seek inter-zone cooperation to achieve more effective zone specialization. A smooth interchange among the zones will greatly improve the overall ISU performance in all provinces. Within zones, negative spillover effects caused by industrial structure convergence among provinces must be avoided. To achieve a synergic development of provincial industries, the authorities must adopt complementary strategies within regions based on the factor endowments, development levels, and industrial structures of each zone.

Acknowledgments

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.physa.2018.08.168.

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