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Article

The Impact of Foreign Direct Investment on Industrialization in China: A Spatial Panel Analysis

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Abstract: This study employs spatial econometric techniques to examine the heterogeneous effects of foreign direct investment (FDI) on industrialization across China's four major regions—East, Central, West, and Northeast—using panel data from 31 provinces (1998–2016). Our findings reveal significant regional variations: FDI negatively impacts industrialization in the developed East, positively influences the less developed Northeast, and shows no significant effect in the Central and Western regions. To achieve balanced industrialization, policymakers should adopt spatially differentiated strategies. In the East, the focus should be on incentivizing high-value FDI in R&D and green technologies, while the Northeast could benefit from stronger economic partnerships within the Belt and Road Initiative (BRI). For the Central and Western regions, prioritizing infrastructure investments linked to the BRI and fostering cross-regional innovation corridors could attract labor-intensive FDI and promote technology diffusion, addressing regional disparities. The study's robust spatial analysis offers valuable guidance for policymakers in crafting region-specific strategies to leverage FDI for balanced economic growth.

Keywords: regional industrialization; foreign direct investment; spatial panel model



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1. Introduction

The relationship between foreign direct investment (FDI) and industrialization has evolved significantly alongside globalization and the rise of regional economic blocs. Early studies, such as [Hiemenz \(1987\)](#), emphasized FDI's catalytic role in Southeast Asia's export-led industrialization, framing it as a cornerstone of economic modernization. However, contemporary research increasingly highlights the transformative influence of multilateral agreements—such as the Regional Comprehensive Economic Partnership (RCEP) and China's Belt and Road Initiative (BRI)—in reshaping FDI flows and industrial trajectories. [Rodríguez-Chávez et al. \(2024\)](#), for instance, demonstrate how such agreements create “investment corridors”, channeling FDI into infrastructure and technology sectors within strategically aligned regions. In China, these dynamics are particularly pronounced: [Wang et al. \(2024\)](#) reveal that BRI-linked infrastructure projects in Western China attract resource-seeking FDI, while RCEP-driven investments in the East prioritize high-tech manufacturing. These bloc-specific patterns align with [García et al. \(2022\)](#), who distinguish between FDI from advanced economies (e.g., the EU and US), which targets innovation hubs, and FDI from developing economies (e.g., ASEAN nations), which favors labor-intensive sectors.

Despite these advancements, significant gaps remain in the literature. First, while studies such as [Liu et al. \(2022\)](#) employ traditional panel models to assess FDI's aggregate effects, they neglect spatial interdependencies—interregional competition and spillovers—that are intrinsic to industrialization processes. Spatial econometric methods, as advocated by [Elhorst \(2014b\)](#), offer a robust solution by modeling these spatial dynamics. Second, despite [Zhao et al.'s \(2024\)](#) analysis of FDI's role in China's high-tech industries, coastal-inland disparities remain underexplored, obscuring the heterogeneous impacts of FDI across regions. Third, few studies explicitly link FDI origins (e.g., BRI vs. RCEP-driven investments) to regional industrialization outcomes, limiting policymakers' ability to tailor strategies to geopolitical and economic realities.

Industrialization itself is a multifaceted process shaped by institutional, technological, and structural factors. [Gerring et al. \(2022\)](#) and [Touré \(2021\)](#) underscore the centrality of regime type and institutional quality, while [Forrest et al. \(2021\)](#) position disruptive innovation—the introduction of transformative technologies or business models—as a catalyst for global industrial leadership. Trade openness ([Trindade, 2005](#); [Meissner & Tang, 2018](#)), consumption patterns ([Ahmad et al., 2020](#); [Echevarria, 1997](#)), and even housing availability ([Dalmazzo et al., 2022](#)) further mediate this process. Yet corporate governance distortions, as [Iacopetta and Peretto \(2021\)](#) argue, can stall industrialization entirely. Against this backdrop, FDI's role remains contested: while [Hiemenz \(1987\)](#) and [Ayunku \(2019\)](#) identify positive long-term relationships between FDI and industrial output in Southeast Asia and Nigeria, respectively, [Gui-Diby and Renard \(2015\)](#) find statistically insignificant effects across 49 African nations. [Rodríguez-Chávez et al. \(2024\)](#) add nuance, noting that despite global FDI growth, developing economies face declining shares, exacerbating uneven development.

Sectoral analyses further complicate this picture. [Orlic et al. \(2018\)](#) reveal that FDI spillovers in European transition economies disproportionately benefit manufacturing firms embedded in knowledge-intensive supply chains, while [Ji \(2019\)](#) warns that FDI in China's secondary industry exacerbates structural imbalances. Conversely, [García et al. \(2022\)](#) and [Tang et al. \(2020\)](#) link FDI to innovation-driven industrialization in Brazil and Chinese cities, respectively, with [Xu et al. \(2024\)](#) and [Zhao et al. \(2024\)](#) emphasizing the synergistic role of two-way FDI in green technological advancement. Studies employing alternative industrial structure metrics—such as the share of the secondary industry ([Shu et al., 2021](#)), the tertiary-to-secondary output ratio ([Liao et al., 2021](#)), or manufacturing industry share ([Ben Mim et al., 2022](#))—further highlight the sectoral complexity of FDI's impacts. Such findings underscore the need for granular, region-specific analyses, particularly in China, where rapid yet uneven growth since the 1970s has created stark regional divides ([Liu et al., 2022](#)).

This study addresses these gaps by examining FDI's heterogeneous impact on industrialization across China's four regions—East, Central, West, and Northeast—using spatial panel data from 1998 to 2016. While prior work focuses on national aggregates ([Rubini et al., 2021](#); [Yang & Li, 2019](#)) or employs limited spatial frameworks ([Gutiérrez-Portilla et al., 2019](#); [Bailey & Warby, 2019](#)), we integrate [Elhorst's \(2014b\)](#) spatial econometrics to model interprovincial spillovers and competition. Our analysis not only reconciles conflicting findings on FDI's role—revealing suppression effects in the advanced East, positive impacts in the lagging Northeast, and null effects elsewhere—but also contextualizes these outcomes within China's participation in BRI and RCEP. Data constraints preclude post-2016 analysis (while national-level data is available till 2022–2023, province-level data on all relevant variables is currently unavailable), yet our findings offer critical insights for policymakers navigating post-pandemic FDI trends and geopolitical realignments.

By applying spatial econometric methods to analyze regional heterogeneity and FDI dynamics driven by economic blocs, this study contributes to theoretical and policy debates on industrialization, offering a framework for leveraging regional cooperation to achieve more balanced and inclusive growth across China's regions.

The remainder of this paper is organized as follows. Section 2 provides the background and also outlines the hypothesis. Section 3 describes the data and variable construction. Section 4 presents and analyses the empirical results. Finally, Section 5 concludes the paper.

2. Background and Research Hypothesis

Industrialization refers to the process by which the proportion of low-level industries in the manufacturing sector gradually decreases, while the proportion of high-level industries increases (Syrquin & Chenery, 1989). Syrquin and Chenery classified industries into three categories: early industries, middle industries, and late industries. During the industrialization process, the proportion of early industries in total output remains unchanged, while the proportion of middle industries increases in the early stages of industrialization but reaches a plateau thereafter. In the later stages of industrialization, the proportion of late industries in total output increases, driving the overall growth of the industrial sector.

In accordance with the classification proposed by Atask et al. (2022b) and the most recent industry classification, we categorize the manufacturing industry into three groups: early industries, middle industries, and late industries.¹ Following the Hoffman coefficient, we define the level of industrialization using an index as follows:

$$\text{indus} = \frac{\text{output of early industries} + \text{output of middle industries}}{\text{output of late industries}} \quad (1)$$

A higher value of the index given by Equation (1) represents a lower level of industrialization in a region.

There are significant differences in economic conditions among the eastern, central, western, and northeast regions of China (Liu et al., 2022), which are mainly reflected in respective levels of economic development. The East has the most advanced economic development level, close to that of western developed countries, followed by the Central, the West, and the Northeast, which are the least developed. For example, in 2021, Guangdong province in the East had a GDP per capita of about RMB ¥98,285 or US \$15,234; Hubei province in the Central had a GDP per capita of about RMB ¥86,416 or US \$13,394; Guangxi province in the West had a GDP per capita of about RMB ¥49,206 or US \$7627; and Liaoning province in the Northeast had a GDP per capita of about RMB ¥65,026 or US \$10,079.

The business environment in the East is the best, with relatively standardized tax collection and deduction, followed by the Central, the Northeast, and the West. For example, in 2016, the marketization index of Guangdong in the East was about 92, the marketization index of Hubei in the Central was about 82, the marketization index of Guangxi in the West was about 77, and the marketization index of Liaoning in the Northeast was about 75.

Therefore, we examine whether the impact of FDI on the industrialization of China's four regions is different. Table 1a,b presents an example of the heterogeneous effects of FDI on regional industrialization, considering the four provinces of Guangdong, Hubei, Guangxi, and Liaoning in China. Guangdong province is located in the developed East region with a high level of industrialization, Hubei province is located in the developing Central region with a middle level of industrialization, and Guangxi and Liaoning provinces are located in the undeveloped West and Northeast regions with low levels of industrialization.

Table 1. The effect of FDI on regional industrialization in selected provinces.

(a) Before FDI (2005)				
Output	Guangdong	Hubei	Guangxi	Liaoning
Early industries (billion ¥)	497.77	102.64	58.15	115.41
Middle industries (billion ¥)	831.34	223.56	94.10	545.02
Late industries (billion ¥)	1733.79	180.59	55.81	246.10
Degree of industrialization	0.77	1.81	2.73	2.68
(b) After FDI (2016)				
Output	Guangdong	Hubei	Guangxi	Liaoning
Early industries (billion ¥)	1926.58	1362.07	570.85	262.67
Middle industries (billion ¥)	3317.46	1572.44	922.62	946.11
Late industries (billion ¥)	6348.19	1485.81	645.11	687.72
Degree of industrialization	0.83	1.98	2.32	1.76
(c) FDI (2005–2016)				
FDI (billion US\$)	Guangdong	Hubei	Guangxi	Liaoning
2005	288.92	25.78	14.71	81.50
2006	314.30	28.00	18.00	94.50
2007	350.71	31.35	21.91	108.77
2008	372.65	34.03	25.83	124.76
2009	393.93	37.72	27.20	131.78
2010	421.26	42.86	27.97	147.62
2011	452.47	51.90	29.94	165.97
2012	478.65	58.27	31.14	185.56
2013	512.64	65.36	31.93	183.21
2014	562.06	77.67	37.40	198.64
2015	644.31	89.23	42.53	206.64
2016	781.57	99.32	43.72	213.28

Note: See Note 1 for definitions of early, middle and late industries.

In panel a of Table 1, the output² of early industries in Guangdong province is 497.77 billion RMB, the output of middle industries in Guangdong province is 831.34 billion RMB, and the output of late industries in Guangdong province is 1733.79 billion RMB. If we use the industrialization index (indus) in Equation (1) as the degree of industrialization, the degree of industrialization in Guangdong province is 0.77. Furthermore, we know that the degree of industrialization in Hubei province is 1.81, the degree of industrialization in Guangxi province is 2.73, and the degree of industrialization in Liaoning province is 2.68.

In panel b of Table 1, we can see that after the introduction of FDI, the output of early industries in Guangdong province was 1926.58 billion RMB, the output of middle industries in Guangdong province was 3317.46 billion RMB, and the output of late industries in Guangdong province was 6348.19 billion RMB. Based on these figures, the degree of industrialization in Guangdong province was calculated to be 0.83.

Additionally, we observe that the degree of industrialization in Hubei province was 1.98, the degree of industrialization in Guangxi province was 2.32, and the degree of industrialization in Liaoning province was 1.76. By comparing the changes in industrialization degree among the four provinces over a period of 11 years, we can see that the degree of industrialization in Guangdong province decreased slightly, the degree of industrialization in Hubei province remained less than 2, the degree of industrialization in Guangxi province remained above 2, and the degree of industrialization in Liaoning province increased significantly.

Looking at panel c of Table 1, we observe that Guangdong province has absorbed much more FDI than other provinces from 2005 to 2016. However, its industrialization degree has decreased slightly during this period. On the other hand, Liaoning province has absorbed more FDI than Hubei and Guangxi provinces, while its industrialization degree has increased significantly. Based on this analysis, we have a hypothesis as follows:

Hypothesis H1: *The effect of FDI on industrialization is negative in the eastern region (considered developed), not significant in the central region (considered developing) or western region (considered undeveloped), and positive in the northeast region (considered undeveloped).*

3. Variables, Data, and Model

3.1. Calculation of the Industrialization Index

As mentioned earlier, we divide China's manufacturing industry into three categories: early industries, middle industries, and late industries, and calculate the industrialization index (*indus*) for China's 31 provinces from 1998 to 2016. The data are sourced from the provincial statistical yearbooks, and Equation (1) is used for the calculations.

3.2. Calculation of FDI

Using the annual RMB exchange rate against the US dollar, we converted the annual FDI of 31 Chinese provinces into its RMB equivalent. We then adjusted it with the fixed asset investment price index and applied a logarithmic transformation to obtain the values of our main independent variable, FDI.

3.3. Control Variables

In addition to FDI, various factors may affect industrialization from the demand perspective, including consumption (Ahmad et al., 2020; Echevarria, 1997), urbanization (Atack et al., 2022a; Hong & Zhang, 2021; Song et al., 2022), trade (Liao et al., 2020; Meissner & Tang, 2018; Trindade, 2005), taxes (Liu et al., 2017; Yoon, 2021), infrastructure (Hu & Xu, 2022), market conditions (Zhou & Xie, 2019; Yu, 2005), and technological innovation (Dai et al., 2022; Forrest et al., 2021; Singh & Chawla, 2018), among others. Therefore, we need to control for these factors in the empirical model.

Thus, we include several control variables in this paper, such as per capita consumption of urban and rural residents, the number of permanent residents, urbanization rate, domestic fixed asset investment, foreign trade level, value-added tax, other taxes, patents, technology market transactions, infrastructure, and marketization index. The definitions of each variable are provided in Table 2.

Table 2. Variable definition.

Variable Type	Variable Description	Variable	Definition
explained variable	industrialization index	<i>indus</i>	$indus = \frac{\text{industrial sales value of early industries} + \text{industrial sales value of middle industries}}{\text{industrial sales value of late industries}}$
independent variables	foreign direct investment	<i>fdi</i>	Using the exchange rate, foreign direct investment is first converted into the local currency and then adjusted for inflation using the fixed asset investment price index. The values of this variable are in logarithmic form.

Table 2. Cont.

Variable Type	Variable Description	Variable	Definition
Control variables	per capita consumption of urban residents	<i>cons_u</i>	The consumption of urban residents is deflated by the consumption price index of urban residents. The values of this variable are in logarithmic form.
	per capita consumption of rural residents	<i>cons_r</i>	The consumption of rural residents is deflated by the retail price index. The values of this variable are in logarithmic form.
	urbanization rate	<i>uratio</i>	Urban population at the end of year divided by the permanent population (%).
	the number of permanent residents	<i>popu</i>	Number of permanent residents. The values of this variable are in logarithmic form.
	domestic fixed asset investment	<i>Inv</i>	The completed amount of fixed asset investment is deflated by the fixed asset investment price index. The values of this variable are in logarithmic form.
	foreign trade level	<i>trade</i>	The import and export volume is converted into local currency values and then deflated by the retail price index. The values of this variable are in logarithmic form.
	value-added tax	<i>vat</i>	Value added tax in logarithmic form.
	other taxes	<i>otax</i>	other tax in logarithmic form.
	patents	<i>patents</i>	Number of domestic patent applications authorized in logarithmic form.
	technology market transaction volume	<i>t_market</i>	The transaction volume of the technology market is deflated by the fixed asset investment price index. The values of this variable are in logarithmic form.
	infrastructure	<i>infra</i>	Highway mileage divided by area.
	marketization index	<i>market</i>	Proportion of non-state employment in urban employment (%).

Descriptive statistics of the main variables are shown in Table 3. The information provided in Table 3 shows that there is considerable variation in the data.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
<i>indus</i>	589	5.4455	8.6161	0.4014	101.5023
<i>fdi</i>	589	7.2311	1.5721	3.0700	10.6200
<i>cons_u</i>	589	3.9900	0.2141	3.5141	4.5758
<i>cons_r</i>	589	3.5604	0.2943	2.9410	4.4078
<i>uratio</i>	589	48.3297	16.1686	17.4366	97.6144
<i>popu</i>	589	3.5018	0.3779	2.4006	4.0758
<i>trade</i>	589	2.9866	0.7991	0.8737	4.8251
<i>inv</i>	589	3.4106	0.5573	1.6309	4.5715
<i>vat</i>	589	2.2651	0.5709	0.3201	3.4756
<i>otax</i>	589	2.4354	0.6189	0.1903	3.7483
<i>patents</i>	589	3.6256	0.7955	0.8451	5.4313
<i>t_market</i>	589	1.2750	0.7845	−1.2304	3.4954
<i>infra</i>	589	0.6330	0.4638	0.0186	2.1091
<i>market</i>	589	61.6145	15.7863	20.5742	92.3596

3.4. Construction of Spatial Weight Matrix

We construct two spatial weight matrices. The first is the adjacent weight matrix (Liu et al., 2022), where the value of the weight matrix element is set to 1 if different provinces share a common boundary, and 0 if there is no common boundary. The diagonal element is set to 0 as well. The second is the geographical distance weight matrix (Gutiérrez-Portilla et al., 2019), which takes the reciprocal of the square of the straight-line distance between the centers of different provinces as the value of the weight matrix elements and sets the diagonal element to 0. We standardize both spatial weight matrices, estimate the model using the adjacent weight matrix, and test the robustness using the geographical distance weight matrix.

It should be noted that thirty-one provinces in China were selected based on the regional division standard of the National Bureau of Statistics of China. These provinces were grouped into four regions: East, Central, West, and Northeast.

3.5. Empirical Model

As we use panel data from thirty-one provinces in China spanning from 1998 to 2016, we begin with an individual and time fixed effects model. However, considering the spatial correlation among different provinces in China, as suggested by studies such as Gutiérrez-Portilla et al. (2019) and Liu et al. (2022), we gradually determine the appropriate spatial panel model. The benchmark fixed effects regression model is as follows:

$$indus_t = sfdi_t + X_t\beta + \mu + \alpha + u_t \quad (2)$$

In Equation (2), the subscript t represents the period, $indus_t$ is the industrialization index, fdi_t is the explanatory variable FDI, and X_t is the vector of control variables, μ captures the region fixed effects, α is the time fixed effects, and u_t is the error term.

Based on estimated residuals from Equation (2) and the spatial weight matrix, we can estimate the Lagrange multiplier spatial lag model test statistics LAG and $R-LAG$ and the Lagrange multiplier spatial error model test statistics ERR and $R-ERR$.³ Elhorst (2014b) pointed out that if the test result is to select the spatial lag model or the spatial error model, or both, a static spatial panel Durbin model should be established (Elhorst, 2014a, 2014b), namely:

$$indus_t = \rho W indus_t + sfdi_t + s' W fdi_t + X_t\beta + W X_t\theta + \mu + \alpha + u_t \quad (3)$$

where W is the spatial weight matrix and ρ is the coefficient of the spatial lag term.

If the error term u_t in Equation (3) satisfies $u_t = \lambda W u_t + \varepsilon_t$, Equation (3) is a spatial panel error model. If the spatial model test results do not satisfy the requirement of the spatial panel autoregressive model or the spatial panel error model at the same time, it is necessary to estimate the spatial panel lag explanatory variable model (Vega & Elhorst, 2015) as follows:

$$indus_t = sfdi_t + s' W fdi_t + X_t\beta + W X_t\theta + \mu + \alpha + u_t \quad (4)$$

Double fixed effects models were established for the four regions of China—the East, the Central, the West, and the Northeast. The estimation results are presented in Table 4.

Table 4 shows that the LM statistics LAG or ERR of four models (models 2, 3 and 4) are significant at the 10% significance level, indicating that they satisfy the requirements of the spatial panel lag model or the spatial panel error model. Therefore, a spatial panel Durbin model needs to be established for the Central, the Western, and the Northeast regions (Elhorst, 2014a, 2014b). In the case of model 1, the LM statistics LAG and ERR are not significant, indicating that model 1 does not meet the requirements of the spatial panel

lag model and the spatial panel error model. Furthermore, as the estimated spatial lag term coefficient ρ and the spatial error autocorrelation coefficient λ are not significant, we need to test for a spatial panel lag explanatory variable model (Vega & Elhorst, 2015). The test result show that the estimated spatial panel lag coefficient s' and θ are jointly significant at the 1% level, which implies that a spatial panel lag explanatory variable model needs to be established for the East region.

Table 4. Spatial autocorrelation test for a double fixed effects model.

Test Statistics	The East	The Central	The West	The Northeast
	(Model 1)	(Model 2)	(Model 3)	(Model 4)
LAG	0.2996	5.3479 **	13.2811 ***	1.1875
R-LAG	0.0445	0.3800	1.9086	5.6106 **
ERR	0.2568	5.2720 **	11.4579 ***	9.5609 ***
R-ERR	0.0017	0.3041	0.0854	13.9841 ***
(SAR)H0: $\rho = 0$	0.3500			
(SEM)H0: $\lambda = 0$	0.4200			
(SDM)H0: $\rho = 0$	0.0200			
(SLX)H0: $s' = \theta = 0$	55.6093 ***			
Individual Fixed Effects	yes	yes	yes	yes
Time Fixed Effects	yes	yes	yes	yes

Note: *** and ** respectively indicate significance at the 1% and 5% levels. SAR represents the spatial panel autoregressive model, SEM represents the spatial panel error model, SDM represents the spatial panel Durbin model, and SLX represents the spatial panel lag explanatory variable model.

4. Empirical Results

4.1. Spatial Panel Model Analysis

In this paper, we employ the spatial panel Durbin model to analyze the data for China, as well as its Central, West, and Northeast regions. However, for the East region, we utilize a spatial panel lag explanatory variable model. To streamline the model, we progressively eliminate insignificant explanatory variables based on the significance of their coefficients. Next, we perform the Wald test, and the estimated results are summarized in Table 5.

Table 5. Spatial panel model estimation.

Explanatory Variables	The East	The Central	The West	The Northeast
	(Model 5)	(Model 6)	(Model 7)	(Model 8)
	SLX	SDM	SDM	SDM
$W \times indus$		−0.5410 *** (0.1151)	−0.4460 *** (0.0958)	−0.3760 *** (0.0925)
fdi	0.8982 *** (0.2045)		−3.1355 ** (1.5198)	−2.3647 *** (0.3820)
$W \times fdi$			6.9058 ** (3.3842)	−2.0007 *** (0.4270)
$cons_u$			−49.3082 *** (9.6917)	−9.5753 *** (1.3772)
$cons_r$				−12.6267 *** (3.1585)
$uratio$	−0.0453 * (0.0182)			0.1856 *** (0.0256)

Table 5. Cont.

Explanatory Variables	The East	The Central	The West	The Northeast
	(Model 5)	(Model 6)	(Model 7)	(Model 8)
	SLX	SDM	SDM	SDM
<i>popu</i>	5.0498 * (2.6088)	−13.9755 *** (5.1325)	95.7408 *** (35.0458)	−81.6831 *** (9.0445)
<i>inv</i>	2.4629 *** (0.7871)		−18.7573 ** (7.9516)	
<i>trade</i>		1.0169 *** (0.3749)		
<i>vat</i>	6.9213 *** (1.3416)	7.0537 ** (0.7687)	70.9160 *** (8.6779)	
<i>otax</i>				−4.2147 *** (1.0574)
<i>patents</i>		−1.0758 *** (0.3888)		7.8880 *** (0.7129)
<i>t_market</i>	−1.4497 *** (0.2703)			
<i>infra</i>	−1.9984 *** (0.4269)		−13.7499 *** (4.2082)	
<i>market</i>		0.0280 *** (0.0126)		
$W \times cons_u$				−13.4342 *** (2.4764)
$W \times cons_r$				−15.7699 *** (3.8598)
$W \times uratio$	−0.0470 *** (0.0243)			0.1967 *** (0.0260)
$W \times popu$	−26.3028 *** (4.7788)	−29.0772 *** (10.2194)		−70.5119 *** (25.4540)
$W \times inv$			−31.1296 * (16.9626)	
$W \times trade$				
$W \times vat$		10.5637 *** (1.3714)		
$W \times otax$				−4.5755 ** (1.5727)
$W \times patents$				3.8544 *** (1.2366)
$W \times t_market$				
$W \times infra$	−1.2237 * (0.7267)		12.8425 (12.2027)	
$W \times market$				
Wald-SAR		63.83 ***	6.55 *	150.93 ***

Table 5. Cont.

Explanatory Variables	The East	The Central	The West	The Northeast
	(Model 5)	(Model 6)	(Model 7)	(Model 8)
	SLX	SDM	SDM	SDM
Wald-SEM		20.98 ***	6.43 **	32.79 ***
J-Sig.Wx	38.6669 ***			
Individual FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj-R ²	0.4274	0.1409	0.3076	0.0664
S ²	0.3790	0.0809	33.0185	0.0219
logL	−172.2927	−20.2405	−727.3941	12.5952

Note: ***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels. The values in the brackets underneath the estimated coefficients are standard errors. SDM represents the Durbin model of the spatial panel and SLX represents the lag explanatory variable model of the spatial panel.

In Table 5, the *Wald-SAR* and *Wald-SEM* statistics of models 6, 7, and 8 are statistically significant, thereby supporting the spatial panel Durbin model. The *J-Sig.Wx* statistic results for model 5 are statistically significant, which supports a spatial panel lag explanatory variable model.

In Table 5, the estimated coefficients of the spatial lag term $W \times \text{indus}$ in models 6, 7, and 8 are statistically significant and negative. Since the industrialization index is a reverse (i.e., the inverted) index, this result implies that This result suggests that industrialization in neighboring provinces negatively affects Chinese provinces in the Central, Western, and Northeastern regions, indicating the presence of industrialization-driven competition among these regions. The estimated coefficient of the spatial lag term $W \times \text{indus}$ of the industrialization index is not significant in model 5, which suggests the absence of industrialization competition between provinces in the East. Foreign Direct Investment (FDI) has different direct effects on industrialization in different regions. It has a negative direct effect on industrialization in the East but a positive direct impact on industrialization in the West and the Northeast. However, FDI has no direct effect on industrialization in the Central region. Additionally, the spatial effect of FDI is negative in the West and positive in the Northeast.

The per capita consumption of urban residents has a positive direct effect on industrialization in the West and the Northeast. However, it has no direct effect on industrialization in the East and the Central regions. The spatial effect of per capita consumption is positive in the Northeast but not significant in the West.

The growth of the population has varying effects in different regions. The spatial effect of population growth is positive in all regions except the West, where it has no spatial effect. Value-added tax has a negative direct effect on industrialization in the East, the Central, and the West regions. The burden of value-added tax is considered high, and tax deductions can promote industrialization. There is tax competition to attract investment and promote industrialization in the West.

Infrastructure has a positive direct effect on industrialization in the East and the West. Infrastructure promotes industrialization in the East by facilitating the flow of talent and capital, while in the West, it mainly expands the production and operation activities of local manufacturing enterprises. The spatial effect of infrastructure is positive in the East but negative in the West. The degree of marketization has little to no effect on industrialization in various regions of China. The overall degree of marketization in China is high, with a significant number of employees working in non-state enterprises.

The direct, spatial, and total effects⁴ of FDI and control variables on the industrialization index are shown in Table 6.

Table 6. The direct, spatial, and total effect of FDI on Regional Industrialization.

Explanatory Variables	Long Term Effect			
	Direct Effect	Spatial Effect	Total Effect	
Model 5	<i>fdi</i>	0.8982 ***	—	0.8982 ***
	<i>uratio</i>	−0.0453 **	−0.0470 *	−0.0923 ***
	<i>popu</i>	5.0498 *	−26.3028 ***	−21.2529 ***
	<i>inv</i>	2.4629 ***	—	2.4629 ***
	<i>vat</i>	6.9213 ***	—	6.9213 ***
	<i>t_market</i>	−1.4497 ***	—	−1.4497 ***
	<i>infra</i>	−1.9984 ***	−1.2237 ***	−3.2221 ***
Model 6	<i>popu</i>	−9.6541 *	−17.7173 **	−27.3714 ***
	<i>trade</i>	1.1198 ***	−0.4639 ***	0.6558 **
	<i>vat</i>	5.7507 ***	5.7034 ***	11.4542 ***
	<i>patents</i>	−1.2095 ***	0.5055 ***	−0.7040 ***
	<i>market</i>	0.0318 **	−0.0135 **	0.0182 **
Model 7	<i>fdi</i>	−3.9024 **	6.5472 **	2.6450
	<i>cons_u</i>	−52.0184 ***	17.3404 ***	−34.6780 ***
	<i>popu</i>	103.9635 ***	−34.8531 **	69.1104 ***
	<i>inv</i>	−16.3734 **	−18.5255	−34.8989 ***
	<i>vat</i>	73.8968 ***	−24.5566 ***	49.3402 ***
	<i>infra</i>	−15.6118 ***	16.8222	0.2104
Model 8	<i>fdi</i>	−2.0269 ***	−1.1166 ***	−3.1436 ***
	<i>cons_u</i>	−6.7308 ***	−9.8481 ***	−16.5789 ***
	<i>cons_r</i>	−9.1484 ***	−11.0305 ***	−20.1789 ***
	<i>uratio</i>	0.1471 ***	0.1279 ***	0.2750 ***
	<i>popu</i>	−69.8662 ***	−38.4656	−108.3318 ***
	<i>otax</i>	−3.2790 ***	−2.9389 **	−6.2179 ***
	<i>patents</i>	7.6554 ***	0.9330	8.5984 ***

Note: ***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels.

Table 6 presents the estimated results, showing that FDI has a significant positive effect on industrialization in the Northeast (Model 8) and a negative effect in the East (Model 5). In Models 6 and 7, FDI has no significant impact on industrialization in the Central and Western regions. These findings confirm our hypothesis and contrast with Hiemenz's (1987) work on Southeast Asian countries.

In the East, FDI shows a negative direct effect and an insignificant spatial effect, resulting in an overall negative impact on industrialization. In contrast, in the Northeast, FDI exhibits both a positive direct and a positive spatial effect, leading to a positive overall impact. In the Central and Western regions, FDI has either insignificant or mixed effects. Specifically, in the West, FDI shows a positive direct effect but a negative spatial effect, resulting in no net impact on industrialization. The varying effects of FDI across regions highlight the importance of regional economic characteristics.

4.1.1. The Role of Economic Development and Business Environment

The spatial effect of FDI on industrialization also varies across regions. In the East and Central regions, where economic development and the business environment are more favorable, the spatial effect of FDI is insignificant. In the West, with a relatively weaker business environment, the spatial effect is negative. However, in the Northeast, despite lower levels of economic development, a favorable business environment and targeted government efforts to attract FDI and promote technological innovation result in a positive spatial effect on industrialization.

4.1.2. Control Variables and Their Impact

The estimation results reveal interesting insights regarding the control variables. First, the control variable t_market is negative and statistically significant in Model 5, indicating that technology market transactions play a crucial role in promoting industrialization, but only in the East. This suggests that technology market transactions facilitate the transfer and adoption of advanced technologies, contributing to industrialization in the East. In contrast, the influence of technology market transactions is not significant in the Central, Western, or Northeast regions. Second, the variable “*patents*” demonstrates varied significance across models. In Model 5, patents are statistically insignificant, suggesting that independent technological innovation in the East does not significantly drive industrialization. Instead, technology market transactions are the primary drivers in this region. However, in Model 6, patents negatively impact industrialization in the Northeast, indicating a disconnect between innovation efforts and productivity in the region. In Model 8, patents have a positive effect on industrialization in the Central region, where independent technological innovation is a key factor in industrial development. Conversely, in Model 7, patents do not have a statistically significant effect in the West, reflecting limited investment in technological innovation in this region.

4.1.3. Comparing Results with Previous Studies

Our findings align with studies that emphasize FDI’s dual role as both a catalyst and disruptor of industrialization. While [Hiemenz \(1987\)](#) observed FDI-driven industrialization in Southeast Asia, our results suggest that advanced regions like China’s East face industrial displacement due to FDI-induced competition, corroborated by [Zhao et al. \(2024\)](#) in high-tech sectors. In contrast, the Northeast’s positive trajectory mirrors [García et al. \(2022\)](#), who link FDI in lagging regions to technology diffusion and state-led revitalization efforts. This contrasts with [Gui-Diby and Renard’s \(2015\)](#) null findings in Africa, highlighting the role of China’s policy-driven FDI absorption mechanisms.

Overall, these estimation results emphasize the nuanced relationship between FDI, control variables, and industrialization across different regions in China. The findings underline the importance of considering regional-specific factors and dynamics when examining the drivers of industrialization.

4.2. Robustness Checks

In this paper, the adjacent weight matrix is selected for robustness testing, and the national and regional models are estimated using the adjacent weight matrix. The estimation results are presented in Table 7.

The estimation results are qualitatively similar to our earlier results; therefore, it can be argued that our main estimation results are reasonably robust.

Table 7. Robustness testing results.

Explanatory Variables	Eastern Region	Central Region	Western Region	Northeast Region
	(Model 9)	(Model 10)	(Model 11)	(Model 12)
	SLX	SDM	SDM	SDM
$W \times indus$		−0.8287 *** (0.1665)	−0.5241 *** (0.1396)	−0.5271 *** (0.1244)
fdi	1.0552 *** (0.2060)		−4.0192 *** (1.5371)	−2.7471 *** (0.5501)
$W \times fdi$			8.1770 * (4.6377)	−3.0702 *** (0.7647)
$cons_u$			−46.1494 *** (9.6893)	−13.8111 *** (2.2412)
$cons_r$				−18.8250 *** (4.7108)
$uratio$	−0.0466 *** (0.0175)			0.2629 *** (0.0406)
$popu$	−3.9399 (2.3887)	−31.8927 *** (7.2138)	79.7874 ** (33.5258)	−102.5659 *** (15.7499)
inv	3.3961 *** (0.7727)		−22.0886 ** (8.9641)	
$trade$		1.3445 *** (0.3741)		
vat	4.7108 *** (1.1990)	7.4465 *** (0.8138)	79.2808 *** (9.6698)	
$otax$				−5.4633 *** (1.5618)
$patents$		−1.4131 *** (0.3892)		8.1586 *** (1.0501)
t_{market}	−1.4521 *** (0.2477)			
$infra$	−1.1352 *** (0.3371)		−8.9795 *** (3.2636)	
$market$		0.0211 ** (0.0127)		
$W \times cons_u$				−21.8625 *** (4.6146)
$W \times cons_r$				−27.7257 *** (7.1368)
$W \times uratio$	−0.0086 (0.0356)			0.3485 *** (0.0527)
$W \times popu$	−31.5207 *** (4.4762)	−72.5827 *** (21.3963)		−116.3263 *** (42.5860)
$W \times inv$			−96.4504 *** (37.5685)	

Table 7. Cont.

Explanatory Variables	Eastern Region	Central Region	Western Region	Northeast Region
	(Model 9)	(Model 10)	(Model 11)	(Model 12)
	SLX	SDM	SDM	SDM
<i>W × trade</i>				
<i>W × vat</i>		11.7756 *** (2.8793)		
<i>W × otax</i>				−7.3102 *** (2.7822)
<i>W × patents</i>				5.8874 *** (2.0859)
<i>W × t_{market}</i>				
<i>W × infra</i>	−2.1708 ** (1.0039)		8.6543 (11.9711)	
<i>W × market</i>				
Wald-SAR		26.72 ***	8.06 **	114.19 ***
Wald-SEM		9.17 **	8.13 **	20.26 ***
J-Sig.Wx	51.3659 ***			
individual	yes	yes	yes	yes
time	yes	yes	yes	yes
Adj-R ²	0.4644	0.1289	0.0031	0.0871
S ²	0.3545	0.0772	34.1203	0.0224
logL	−165.9432	−27.9318	−729.9567	18.3737

Note: ***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels.

5. Concluding Remarks

This paper employs a spatial panel model to examine the heterogeneous impact of Foreign Direct Investment (FDI) on industrialization across China's four major regions—East, Central, West, and Northeast. The findings, based on data over the 1988–2016 period, reveal significant regional disparities: while FDI suppresses industrialization in the economically advanced East, it fosters industrial development in the less-developed Northeast and exhibits no statistically significant effect in the Central and Western regions. These results underscore the critical role of regional development stages, institutional frameworks, and spatial interdependencies in shaping the industrial outcomes of FDI.

The study challenges the conventional perspective of FDI as a uniform driver of industrialization. Whereas prior research (e.g., [Hiemenz, 1987](#); [Gui-Diby & Renard, 2015](#)) emphasizes the aggregate benefits of FDI, our analysis demonstrates that its impact is highly contingent upon regional contexts. The negative effect observed in the East aligns with [Zhao et al. \(2024\)](#), who attribute this phenomenon to FDI-driven competition displacing low-tech industries. Conversely, the positive effect in the Northeast is consistent with [García et al. \(2022\)](#), where lagging regions leverage FDI as a mechanism for technological catch-up. Methodologically, this study advances existing analyses by employing spatial

econometrics (Elhorst, 2014b), which allows for the identification of interprovincial spillover effects—an aspect largely overlooked in prior China-focused research.

The findings presented in this paper have significant policy implications for regional industrial development in China. To achieve balanced industrialization, policymakers must adopt spatially differentiated strategies. In the East, policy measures should focus on redirecting incentives toward high-value FDI in research and development (R&D) and green technologies to counteract industrial displacement. Tax incentives for innovation hubs, as proposed by Xu et al. (2024), may help mitigate negative spillovers. In the North-east, fostering stronger economic partnerships with Northeast Asian economies (e.g., South Korea, Russia) within the framework of the Belt and Road Initiative (BRI) could sustain FDI inflows and enhance infrastructure development. For the Central and Western regions, prioritizing BRI-linked infrastructure investments could attract labor-intensive FDI while addressing institutional gaps that currently diminish FDI benefits. Furthermore, strengthening cross-regional coordination through the establishment of innovation corridors could facilitate technology diffusion between the East and inland provinces, promoting more balanced industrial growth.

Despite the contributions of this study, certain limitations should be acknowledged. The analysis is constrained by its pre-2016 timeframe, thereby excluding more recent disruptions such as the U.S.–China trade war, the COVID-19 pandemic, and accelerated BRI investments. Post-pandemic FDI surges in the technology and healthcare sectors (Efthimiou, 2024) may further exacerbate negative industrial trends in the East, while increased BRI infrastructure development in the West could enhance future spillover effects. Additionally, limitations in provincial-level data precluded a detailed analysis of FDI origin heterogeneity (e.g., OECD vs. non-OECD sources), a critical factor in bloc-driven industrialization dynamics.

Future research should extend this analysis using post-2020 data to assess the long-term impact of geopolitical shifts and pandemic-era FDI trends. Disaggregating FDI by origin (e.g., BRI vs. Regional Comprehensive Economic Partnership [RCEP] partners) and by sector (e.g., green vs. traditional industries) would provide deeper insights into region-specific industrialization pathways.

By integrating spatial econometrics with an analysis of regional heterogeneity, this study redefines the role of FDI in China's industrialization, offering a nuanced framework for policymakers to leverage multilateral economic blocs while addressing spatial inequalities. As global FDI patterns continue to evolve amid increasing geopolitical fragmentation, spatially informed strategies will be crucial for achieving sustainable and equitable industrial development.

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Notes

- 1 Specifically, early industries encompass 9 industries, including agricultural and sideline food processing industry, food manufacturing industry, beverage manufacturing industry, tobacco products industry, textile industry, textile clothing shoes and hats manufacturing industry, leather, fur, feather (fluff) and its products industry, wood processing and bamboo, rattan, palm and grass products industry, and furniture manufacturing industry. Middle industries encompass 9 industries, including petroleum processing and coking and nuclear fuel processing, chemical raw materials and chemical products manufacturing, pharmaceutical manufacturing, chemical fibre manufacturing, rubber and plastic products, non-metallic mineral products, ferrous metal smelting and rolling processing, non-ferrous metal smelting and rolling processing, and metal products. Late industries encompass 6 industries, including general equipment manufacturing, special equipment manufacturing, transportation equipment manufacturing (including automobile manufacturing and railway, shipbuilding, aerospace and other transportation equipment manufacturing), electrical machinery and equipment manufacturing, computer communication and other electronic equipment manufacturing, and instrumentation and cultural office machinery manufacturing.
- 2 We use the industrial sales value as a proxy for the output of industries to calculate the industrialization index because there is no industry GDP data available for China's provinces.
- 3 LAG and R-LAG, respectively, are the Lagrange multiplier spatial lag model and robust spatial lag model test statistic. A significant statistic suggests that there is spatial autocorrelation in the model residuals, which may require the use of a spatial error model instead. *ERR* (error regression residuals) is the Lagrange multiplier test statistics for a spatial error model, which is used to test for spatial autocorrelation in the residuals of the model. *R-ERR* (Robust *ERR*) is a variant of the test statistics for a spatial error model that is robust to heteroscedasticity and spatial autocorrelation in the errors. This test is useful when the spatial error model assumes homoscedasticity and spatial independence, but the actual data exhibit heteroscedasticity and spatial autocorrelation. The *R-ERR* test can provide more reliable results in such situations (Elhorst, 2014b).
- 4 The coefficients s and β measure the direct effect of the variables fdi_t and X_t on the explained variable $indust_t$, while the coefficients s' and θ measure the local spatial effect of the variables fdi_t and X_t on the explained variable $indust_t$. The coefficient sp measure the global spatial effect of the variables fdi_t and X_t on the explained variable $indust_t$. The total effect is the sum of the direct effect and the spatial effect.

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