FDI, Spatial Effects and Green Total Factor Productivity in the Context of the Digital Economy: A Case Study of 281 Prefecture-Level Cities in China

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Abstract. The manufacturing sector's sustained openness post high-end and digital transformation is a key driver for regional green development in the digital economy era. Using Data Envelopment Analysis and GML index, we examined the green total factor productivity in 281 Chinese prefecture-level cities from 2011 to 2020. Spatial characteristics were assessed using the Moran's I, and spatial econometric methods were applied to explore the impact of manufacturing FDI on regional green total factor productivity. Findings indicate spatial agglomeration of GTFP, with FDI in manufacturing significantly promoting it, accompanied by negative spatial spillover effects. Heterogeneous analysis reveals a stronger effect in the central region compared to the east and more pronounced negative effects in the west.

Keywords: digital economy, manufacturing FDI, spatial effect, green total factor productivity.

1 Introduction

In the context of the digital economy, economic growth is shifting from the traditional investment-driven model to the total factor productivity-driven model, and residents' demand for environmental quality is greater[1], which is consistent with the implementation of green development principles. GTFP is affected by inter-regional economic linkages and has certain spatial characteristics. How to promote the green development of regional economy has become an important issue of concern to the academic community. As the foundation of the real economy, the opening up of the manufacturing industry is conducive to improving the efficiency of energy use[2] and guiding technological iteration into a positive cycle[3]. In the digital era, new concepts drive innovation, industry clustering, and prompt the manufacturing sector to absorb Foreign Direct Investment (FDI) relying on advanced factors like technology and talent. Data from the Chinese Ministry of Commerce reveals a 100.3% increase in actual utilized foreign

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investment in China's high-tech manufacturing in 2022 compared to 2012, emphasizing the pivotal role of FDI in high-end industrialization, low-carbon energy, and resource circulation.

This paper, using panel data from 281 Chinese prefecture-level cities (2011–2020), employs spatial econometric models to investigate the relationship between manufacturing FDI and regional economic GTFP. Departing from existing literature, our research, anchored in the digital economy context, explores the temporal evolution, regional variations, and impact pathways of manufacturing FDI transitioning to high-end development on regional economic GTFP. The aim is to offer nuanced, policy-oriented support for the coordinated development of regional economies and the synergistic enhancement of environmental protection.

2 Literature review

Enhancing GTFP underscores the central focus on improving the quality of economic growth[4]. Academic inquiry into GTFP influencing factors encompasses diverse perspectives, centering on economic policies[5], technological progress[6], and environmental policies[7]. In the digital economy era, China's industrial restructuring and upgrading, particularly in the continuous advancement of high-end manufacturing and deep optimization, along with initiatives like "the Belt and Road," are expanding the openness of the manufacturing sector[8]. This dynamic may reshape the impact direction, pathways, and levels of traditional manufacturing FDI on GTFP.

Academic research predominantly employs fixed-effects models[9], difference-in-differences methods[10], and other approaches to investigate the influencing factors of GTFP. However, these methods often overlook the inter-regional economic interconnectivity and spatial characteristics of green development. In contrast, spatial econometric models consider both direct effects and spatial effects arising from regional economic geography.

While existing research has extensively explored green development, the ongoing transformation, upgrading, and continuous openness of the manufacturing sector in the digital economy era may introduce new influences on GTFP through factors like industry and location. However, this aspect remains relatively underexplored. This paper, anchored in the digital economy era's new perspective and considering the spatial characteristics of regional economies, assesses the impact of FDI on regional GTFP following the significant transformation of manufacturing towards high-end development. The findings aim to provide more precise and specific policy recommendations for regional development.

3 Research design

3.1 Model Construction and Variable Clarification

In this paper, we use Data Envelopment Analysis-Slack Based Measure (DEA-SBM) and Global Malmquist-Luenberger (GML) index to construct GTFP, and analyze the spatial characteristics of GTFP based on Moran's I. To analyze the spatial characteristics of GTFP, using spatial econometric models to measure the path and degree of influence of manufacturing FDI on GTFP, and finally conducting heterogeneity tests to further analyze the differences in the influence of different regions.

1. DEA-SBM model and Moran's I.

Table 1 outlines the selected indicators for input-output in DEA. Capital input focuses on fixed asset investment, measured by the Fixed Asset Price Deflation Index, following the methodology proposed by Zhang et al. (2004)[11]. For expected output, Gross Domestic Product (GDP) is chosen and normalized to the base year 2000, aligning with the approach by Zhang et al. (2004)[1].

Table 1. GTFP Measurement Indicators

goal	angle on sth	infrastructural	norm
Green Total Elemental Productivity	throw oneself into	resource (such as manpower or tourism)	Land area for urban construction
		resource (such as manpower or tourism)	Electricity consumption of society as a whole
		principal	Price deflator for investment in fixed assets
		labor force	Number of employees in the unit at the end of the year
	Expected outputs	Economic developments	gross domestic product (GDP)
	Non-expected outputs	industrial waste water	Industrial wastewater discharge
		industrial waste gas	Annual average concentration of PM2.5
		sludge	Industrial sulphur dioxide emissions

Moran's I is used to measure the spatial autocorrelation of GTFP in Chinese cities, which can clearly indicate the spatial aggregation of GTFP in Chinese cities. An economic spatial weight matrix W is defined to describe the spatial dependence between 281 cities in China and normalized, whereW_{ij} represents the degree of influence of city i on city j, and the specific formula is as follows:

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1i} \\ W_{21} & W_{22} & \cdots & W_{2i} \\ \vdots & \vdots & \cdots & \vdots \\ W_{i1} & W_{i2} & \cdots & W_{ii} \end{bmatrix} \tag{1}$$

Where i and j are the number of selected Chinese cities 281. In order to clearly observe the local spatial aggregation characteristics of each city, this paper observes the global Moran's I, which is measured using ArcGIS software.

2. Spatial Durbin model.

To ensure research consistency, the aforementioned W matrix is employed as the parameter matrix for measuring spatial effects. LM, LR, and Hausman tests are sequentially conducted on existing data. Based on the test results, a spatial Durbin model is constructed with the specific formula as follows:

$$GTFP_{i,t} = \alpha_0 + \rho WGTFP_{i,t} + \phi_1 WF_{i,t} + \alpha_1 F_{i,t} + \phi_2 WCON_{i,t} + \alpha_2 CON_{i,t} + \varepsilon_{i,t} \quad (2)$$

Where $GTFP_{i,t}$ is the GTFP of city i in period t; $F_{i,t}$ is the level of manufacturing FDI in city i in period t; W is the spatial weight matrix; ρ is the spatial autoregressive coefficient; $CON_{i,t}$ is a set of control variables; α_0 is the intercept term; $\alpha_1$and α_2 are the regression coefficients of manufacturing FDI and control variables, respectively; $\phi_1$andϕ_2 are the elasticity coefficients of the spatial interaction terms of manufacturing FDI and control variables; and $\varepsilon_{i,t}$ denotes the random perturbation term. The variables are normalized to avoid the influence of different scales. All variables used in the spatial measurement model are shown in Table 2:

Table 2. Spatial measurement model variables

Variable type	variable name	variable symbol	Description of variables
explanatory variable	GTFP	GTFP	Measured using the DEA-SBM model as well as the LM index
explanatory variable	Liberalization of the manufacturing sector	F	281 prefecture-level cities, 2012-2020 Manufacturing FDI
control variable	Level of economic development	lnGDP	Logarithm of GDP per capita in 281 prefecture-level cities
	Intensity of environmental regulation	EN	Number of word frequencies for environmental vocabulary Ratio of word frequency of government work reports to those of prefecture-level cities
	Trade openness	DOT	Total trade exports and imports
	educational level	DOE	Expenditure on education as a share of urban GDP
	Level of development of the digital economy	DE	Digital Inclusive Finance Index

3.2 Samples and Data Sources

This paper examines a sample of 281 cities in China from 2011 to 2020. Due to data availability constraints, certain areas like Tibet, specific cities in Xinjiang and Qinghai, and Laiwu City in Shandong Province are excluded. The original PM2.5 data are sourced from Dalhousie University's Atmospheric Composition Analysis Group. City coordinates for constructing the spatial weight matrix come from the National Bureau of Statistics. Environmental regulation intensity is derived from the frequency of environmental terms in government work reports. Green patent data are obtained from the China Research Data Service Platform and the National Intellectual Property Database.

The China Digital Inclusive Finance Index is sourced from Peking University Digital Finance Research Center and Ant Financial Group. Other data are from the respective year's "China City Statistical Yearbook." To address missing data and standardize absolute values, interpolation and normalization are applied, respectively.

4 Empirical tests of spatial measurement and analysis of results

4.1 Moran's I results

The global Moran's I for GTFP in 281 Chinese cities from 2012 to 2020 are 0.117, 0.025, 0.074, 0.094, 0.032, 0.089, 0.133, 0.252, and 0.230. Except for the year 2013, Moran's I for all cities is positive at the 1% significance level. This indicates a strong spatial spillover effect in GTFP among Chinese prefecture-level cities, demonstrating clear spatial autocorrelation characteristics across regions.

4.2 Spatial econometric modeling results

Following Moran's I, LR test, Hausman test, and robustness checks, an individual fixed-effects spatial Durbin model was chosen (Table 3). The second column shows a positive correlation between local manufacturing FDI and GTFP at a 1% significance level, with a direct effect coefficient of 0.574. This indicates that a one-unit increase in local manufacturing FDI results in a 0.574 unit increase in GTFP. In the third column, at a 10% significance level, a negative correlation is observed between manufacturing FDI in other cities and GTFP in the focal city, with an indirect effect coefficient of 0.929. This implies that a one-unit increase in manufacturing FDI in other cities leads to a 0.929 unit decrease in GTFP in the focal city.

Table 3. Results of spatial Durbin measures

variant	(1) main effect	(2) spillover effect
F	0.574***	-0.929*
	(0.222)	(0.543)
control variables	Yes	Yes
urban fixed effect	Yes	Yes
Year fixed effects	Yes	Yes
rho	0.468***	
	(0.029)	
sigma2_e	0.011***	0.011***
	(0.000)	(0.000)
sample size	2,529	2,529
R^2(be) worth	0.066	0.066

Note: *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively, with standard errors in parentheses.

4.3 Endogeneity test

Adopting the approach of Xu[12], nightlight VIIRS data serves as the instrumental variable for endogeneity testing. Results reveal a significantly positive main effect at the 1% level, with a Kleibergen-Paap Wald rk F value of 17.357, surpassing the critical value of 8.96 at the 15% level. This confirms the absence of a weak instrumental variable problem, affirming the positive impact of Manufacturing FDI on GTFP.

4.4 Robustness Test

To ensure robust conclusions, spatial regressions were applied to urban data from 2016 to 2020. The results reveal a highly significant positive correlation (at the 1% level) between local manufacturing FDI and GTFP during 2016-2020, with a coefficient of 0.983. Moreover, a significant negative correlation (at the 10% level) is observed between manufacturing FDI in other cities and GTFP in the focal city, with a coefficient of -1.646. This finding reinforces the earlier conclusion.

4.5 Heterogeneity Test

Heterogeneity in factor endowments and industrial structures leads to diverse impact pathways for GTFP. Following the approach of Shen et al.[13], China is stratified into East, Central, and West regions. The relationship between manufacturing FDI and GTFP is examined in each regional city, yielding results presented in Table 4. The data in the third and fourth columns highlight a significant positive correlation between manufacturing FDI and GTFP in the Central region. The last two columns underscore the notable presence of spatial spillover effects between manufacturing FDI and GTFP in the Western region.

Table 4. Results of heterogeneity test

	landlord		center		west	
	(1)	(2)	(3)	(4)	(5)	(6)
variant	main effect	spillover effect	main effect	spillover effect	main effect	spillover effect
F	0.222	-0.721	0.494**	-1.143	0.384	6.817**
	(0.406)	(0.690)	(0.241)	(0.748)	(0.886)	(3.083)
control variable	Yes	Yes	Yes	Yes	Yes	Yes
urban fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
rho	0.305***	0.305***	0.428***	0.428***	0.189***	0.189***
	(0.044)	(0.044)	(0.049)	(0.049)	(0.069)	(0.069)
sigma2_e	0.017***	0.017***	0.006***	0.006***	0.010***	0.010***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
sample size	900	900	891	891	738	738
R^2(be) worth	0.147	0.147	0.018	0.018	0.074	0.074

Note: Same as table 1.

5 Conclusions

In the era of the digital economy, the manufacturing sector's shift towards high-end upgrading presents a key opportunity for regional economic integration, deepened technological exchange, and sustainable development through continual absorption of FDI. Employing the GTFP indicator, this study, using a spatial econometric model, examines the relationship between manufacturing FDI and GTFP. The findings are as follows: Firstly, during 2012-2020, the absorption of FDI by the manufacturing sector in Chinese cities positively impacts GTFP. Continuous FDI absorption fosters environmentally friendly production technologies, spurs technology spillovers, and improves resource utilization efficiency. Secondly, a spatial effect exists between manufacturing FDI and GTFP. The GTFP of the focal city is negatively affected by manufacturing FDI in other cities, influencing both technology spillovers and the GTFP of surrounding areas. Thirdly, heterogeneity tests reveal that cities in the Western region experience a significant adverse impact on GTFP from manufacturing FDI in other cities, while cities in the Central region notably benefit from the positive impact of local manufacturing FDI.

Based on the foregoing findings, this paper proposes the following policy recommendations: 1. Spatially-Informed Policy Adjustments for Manufacturing Sector Transformation： Conduct real-time adjustments to policies related to the high-end transformation of the manufacturing sector by comprehensively understanding spatial agglomeration and dynamic evolution in regional green economic development. This transformation requires support from both high-tech advancements and a diverse pool of top-tier talents. 2. Focus on Manufacturing FDI's Role in Green Development during the Digital Economy Era: Implement encouraging policies to sustainably opening up the manufacturing industry, recognizing the pivotal role of Manufacturing FDI in promoting regional GTFP during the digital economy era. Streamline the pathway for manufacturing industry openness and enhance risk management capabilities. 3.Mitigate Spatial Imbalances in Manufacturing Openness and Green Development: Address spatial imbalances in regional manufacturing openness and strive for high-quality green development. Accelerate the digital transformation of traditional industries in central and western regions, leveraging local industrial advantages and exploring the potential for sustainable development. Harness technological spillover effects from the eastern region's rapid development, establishing diverse investment models for economic stimulation in the central and western regions.

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