

Two-Way FDI, Absorptive Thresholds, and Total Factor Productivity Growth in Service Sector

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Abstract

Based on provincial panel data from 30 Chinese provinces over the period 2008-2023, this paper examines the spatial spillover effects of two-way FDI on service sector total factor productivity (TFP) growth within a spatial econometric framework, and constructs a panel threshold model to test the nonlinear constraints imposed by absorptive capacity. The findings are as follows. First, the spatial spillover effects of service sector IFDI and OFDI depend on the specification of the spatial weight matrix: the indirect effect is significantly positive under the geographic distance matrix, becomes insignificant for IFDI under the economic distance matrix, and is most pronounced under the absorptive capacity distance matrix, suggesting that spillover transmission depends on the spatial proximity of absorptive capacity rather than geographic or economic proximity. Second, the productivity spillovers of two-way FDI exhibit significant absorptive capacity thresholds, with human capital thresholds at 0.106 and 0.251, and R&D intensity thresholds at 0.012 and 0.028. Third, the absorptive threshold for producer services is lower than that for consumer services, a difference attributable to the vertical industrial linkages between producer services and manufacturing. This paper extends absorptive capacity threshold analysis to the service sector and identifies absorption mechanisms distinctive to services.

Keywords

Two-Way FDI, Service Sector TFP Growth, Spatial Spillover, Absorptive Capacity, Threshold Effect

1. Introduction

The service sector is a vital component of a modern industrial system, and en-

hancing its total factor productivity (TFP) growth is a central pillar of China's pursuit of high-quality economic development. As opening-up deepens, foreign direct investment (IFDI) flows into the service sector, while outward foreign direct investment (OFDI) in services continues to expand. Traditional international investment theory posits that foreign capital brings technology and managerial expertise that generate positive spillovers (Coe & Helpman, 1995). However, a substantial body of subsequent research has found that FDI spillover effects are uncertain and that not all regions can equally capture external technological dividends (Borensztein et al., 1998).

Existing literature has established that absorptive capacity is the core condition determining whether technology spillovers materialize. Chen et al. (2020) employed a spatial econometric model to examine the spatial spillover effects of two-way service sector FDI on service sector TFP, and made an important finding: under the economic weight matrix, the inter-regional effect of service sector FDI is insignificant, while service sector OFDI has a significantly negative intra-regional effect and a significantly positive inter-regional spillover effect. This finding raises a question that has not yet been answered: why do spatial spillover effects depend on the specification of the weight matrix, and why does the inter-regional spillover of FDI disappear under certain specifications? This paper argues that the answer lies in the heterogeneity of absorptive capacity—the existence of spillovers has been verified, but the conditions under which spillovers take effect have not been systematically examined.

Compared with Chen et al. (2020), this paper makes three incremental contributions. First, it extends absorptive capacity threshold analysis from the manufacturing and aggregate economy context to the service sector, examining the distinctive absorption mechanisms of services. Second, it distinguishes the threshold differences between two types of absorptive capacity: human capital and R&D intensity. Third, it explores the threshold heterogeneity between producer services and consumer services.

2. Literature Review and Theoretical Mechanisms

2.1. Literature Review

In the classical literature on international investment spillovers, Coe and Helpman (1995) demonstrated that international R&D spillovers through import channels can enhance domestic productivity. Borensztein et al. (1998) were the first to propose that human capital determines the effectiveness of FDI technology absorption, and that FDI can only exert a positive effect once human capital reaches a certain level. He et al. (2014) employed a non-parametric DEA method to measure TFP and used a threshold regression model to find that FDI technology spillovers exhibit nonlinear threshold effects with respect to four factors: economic development level, trade dependence, infrastructure construction, and human capital level. Zhao and Gu (2006) verified the R&D stock threshold characteristics of OFDI reverse technology spillovers.

Chinese scholars have conducted extensive research on FDI and service sector TFP. Within the two-way FDI framework, the contribution of [Chen et al. \(2020\)](#) is most directly relevant: that study used a spatial econometric model and found that the productivity effects of service sector FDI and OFDI exhibit significant spatial dependence, with conclusions varying across different weight matrices. This variation itself constitutes the research motivation of the present paper.

Regarding absorptive capacity thresholds in the service sector, [Xu and Liu \(2023\)](#) found that both dimensions of absorptive capacity—R&D employee input and R&D expenditure input—exhibit two threshold values, and that as these inputs increase, the positive spillover effect of FDI on service sector independent innovation strengthens continuously. This finding provides direct support for the present paper's distinction between human capital and R&D intensity thresholds.

Existing research generally acknowledges the moderating role of absorptive capacity, but two limitations remain. First, [Chen et al. \(2020\)](#) verified the existence of spatial spillovers but did not answer why spillovers disappear under certain spatial specifications. Second, research on absorptive capacity thresholds in the service sector remains insufficient, particularly regarding the threshold differences between producer services and consumer services.

2.2. Theoretical Mechanisms and Research Hypotheses

Mechanism 1: Spatial spillover effects of two-way FDI

IFDI transmits technology and managerial expertise to local services through demonstration effects, labor mobility, and industrial linkages. OFDI acquires overseas technology and market information through foreign subsidiaries, transmits it back to the home province, and generates cross-regional spillovers through regional economic linkages.

However, the findings of [Chen et al. \(2020\)](#) suggest that the direction and significance of spatial spillovers depend on the specification of the spatial weight matrix. The insignificance of the inter-regional FDI effect under the economic distance matrix carries a theoretical implication: the spatial transmission of technology spillovers does not occur automatically but is constrained by the proximity of absorptive capacity across regions. If neighboring provinces lack sufficient absorptive capacity, technology spillovers will fail to materialize even in the presence of geographic proximity; economic similarity alone is insufficient to guarantee the spatial transmission of technology spillovers. Accordingly, we propose:

H1: Service sector IFDI and OFDI have positive effects on local service sector TFP growth. The spatial spillover effects are significant under geographic proximity and absorptive capacity proximity, but not under economic proximity. The spillover effects under absorptive capacity proximity are stronger than those under geographic proximity.

Mechanism 2: Threshold constraints of absorptive capacity

Regional absorptive capacity comprises two dimensions: human capital and R&D investment. When absorptive capacity falls below the threshold, local firms

lack the ability to learn from and assimilate foreign technology, making it difficult to transform the knowledge brought by foreign capital, and spillover effects are insignificant (Girma, 2005). When absorptive capacity crosses the threshold range, local actors possess the capacity for assimilation, imitation, and secondary innovation, and the positive spillovers of two-way FDI strengthen significantly. When absorptive capacity is excessively high, the technological gap between local and overseas firms narrows, the space for technological catch-up shrinks, and the spillover dividend exhibits diminishing marginal returns.

Borensztein et al. (1998) focused on the human capital stock threshold, whereas the distinctive feature of absorptive capacity in the service sector context is that technology spillovers in services depend more on R&D employee input (a dimension of human capital quality) than on R&D expenditure input alone. Xu and Liu (2023) found that both R&D employee input and R&D expenditure input exhibit threshold values, but their policy implications differ—the former reflects human capital accumulation, while the latter reflects capital investment. Accordingly, we propose:

H2: The spillover effects of two-way FDI on service sector TFP growth exhibit threshold effects based on absorptive capacity, with spillover effects varying non-linearly with the level of absorptive capacity. The threshold values for human capital and R&D intensity differ.

Mechanism 3: Structural heterogeneity within the service sector

The internal structure of the service sector varies significantly. Producer services (finance, logistics, information services) are more technology- and knowledge-intensive and have stronger industrial linkages with manufacturing (Fernandes & Paunov, 2012). Qian (2019) identified a noteworthy phenomenon: in the producer services sector, the negative horizontal spillover effect of FDI is larger, which is explained by the excessive technological gap between domestic and foreign firms that prevents spillovers from being absorbed. However, this finding is in tension with the inference that producer services have a higher absorption threshold.

This paper argues that the key to resolving this tension lies in distinguishing between horizontal spillovers and vertical spillovers (Javorcik, 2004). Although producer services face a larger technological gap and greater competitive pressure (negative horizontal spillovers), they obtain technology transfer more efficiently through vertical spillover channels (forward and backward industrial linkages with manufacturing) (Blalock & Gertler, 2008). The differentiated intermediate inputs provided by multinational producer service firms increase the variety of intermediate inputs in manufacturing production processes, and this variety expansion effect is itself an important channel of technology spillovers. Therefore, the absorption threshold for producer services may be lower than that for consumer services, because vertical spillover channels reduce the initial R&D investment required for absorption. Accordingly, we propose:

H3: The absorption threshold for producer services is lower than that for consumer services, and this difference is attributable to the vertical industrial linkages between producer services and manufacturing, which enable technology spillo-

vers through learning by doing.

3. Research Design

3.1. Sample and Data

We select a panel of 30 Chinese provinces (excluding Xizang) over the period 2008-2023. For provincial service-sector IFDI, we use the China Statistical Yearbook series on actually utilized foreign direct investment by industry. We retain industries classified as service sectors under the GB/T 4754-2017 national industry classification, aggregate their actually utilized foreign capital to the provincial service-sector total, and convert USD-denominated values into RMB using the annual average exchange rate. For provincial service-sector OFDI, we use the Statistical Bulletin of China's Outward Foreign Direct Investment series on outward FDI flows by industry. We similarly retain service-sector industries, aggregate them to the provincial service-sector total, and convert to RMB. When a province-industry cell is missing, we first interpolate linearly within the province-industry series; if interpolation is not possible, we replace the missing value with the province-industry mean over the sample period. For positive flows, we take the natural logarithm after aggregation. For zero or negative flows, we use the inverse hyperbolic sine transformation instead of the natural logarithm; this preserves zero and negative values and approximates the log transformation for large positive values. The same treatment is applied to both IFDI and OFDI. Absorptive capacity proxies are human capital (HC, the share of the population with a college education or above, sourced from the China Population and Employment Statistics Yearbook) and R&D intensity (RD, R&D expenditure as a share of GDP, sourced from the China Statistical Yearbook on Science and Technology). Control variables include economic development level (PGDP, log of per capita GDP), openness (OPEN, total imports and exports as a share of GDP), government intervention (GOV, local fiscal expenditure as a share of GDP), marketization (MKT, Fan Gang marketization index), financial development (FIN, financial institution loan balance as a share of GDP), and infrastructure (INF, internet penetration rate). Continuous variables are winsorized at the 1% level. **Table A1** in the Appendix provides detailed variable definitions and data sources.

3.2. Measurement of the Dependent Variable

Service sector TFP growth is measured using the DEA-Malmquist index. Input variables are service sector employment and service sector capital stock (perpetual inventory method, depreciation rate 9.6%). The output variable is service sector value added (constant prices, base year 2008). The DEA model is specified as an input-oriented model with variable returns to scale (VRS).

It should be noted that the DEA-Malmquist index measures the rate of TFP change, not the TFP level. The dependent variable in this paper is the rate of TFP change, and the language of the hypotheses and conclusions is consistent with this throughout.

As a robustness check, we use the Levinsohn-Petrin (LP) method to estimate the provincial service sector TFP level. The LP method uses service sector intermediate inputs as a proxy for productivity shocks, effectively eliminating endogeneity and selection bias in OLS regressions. The input variables are service sector employment (labor), service sector capital stock (capital), and service sector intermediate inputs (proxy variable). The output variable is service sector value added. The LP method produces an estimate of the logarithmic level of TFP, denoted $\ln TFP_{it}^{LP}$. To ensure comparability with the DEA-Malmquist index (which measures TFP change), we use the first difference of the LP-based TFP level, $\Delta \ln TFP_{it}^{LP} = \ln TFP_{it}^{LP} - \ln TFP_{i,t-1}^{LP}$, as the alternative dependent variable. This first difference approximates the rate of TFP change and is therefore conceptually comparable to the DEA-Malmquist index. The correlation between $\Delta \ln TFP_{it}^{LP}$ and the DEA-Malmquist index is 0.72, indicating satisfactory comparability between the two measures.

3.3. Variable Definitions

Table A1 in the Appendix provides the definitions and data sources for all variables used in the empirical analysis. The dependent variable is the service sector TFP change rate, measured by the DEA-Malmquist index. The core explanatory variables are service sector IFDI and OFDI, both logged. The threshold variables are human capital (HC) and R&D intensity (RD). Control variables include economic development level, openness, government intervention, marketization, financial development, and infrastructure.

3.4. Model Specification

1) Spatial Durbin Model (SDM)

$$TFP_{it} = \rho W TFP_{it} + \beta_1 IFDI_{it} + \beta_2 OFDI_{it} + \gamma X_{it} + \theta W \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where W is the spatial weight matrix, specified alternatively as the geographic distance matrix, the economic distance matrix, and the absorptive capacity distance matrix. ρ is the spatial autocorrelation coefficient; X is the vector of control variables; μ_i denotes individual fixed effects; and λ_t denotes time fixed effects.

Before estimating the SDM, we conduct diagnostic tests to justify the model specification. The Lagrange Multiplier (LM) tests for spatial lag and spatial error dependence both reject the null of no spatial dependence at the 1% level, supporting the inclusion of spatial terms. The Hausman test rejects the null of random effects ($p < 0.01$), supporting the fixed effects specification. The Likelihood Ratio (LR) test for the SDM against the spatial autoregressive (SAR) and spatial error (SEM) alternatives rejects both restricted specifications, confirming the SDM as the appropriate model. Residual spatial autocorrelation tests (Moran's I on residuals) do not reject the null of no remaining spatial dependence, indicating that the SDM adequately captures the spatial structure in the data.

The economic distance matrix is defined as:

$$W_{ij}^{econ} = \frac{1}{|\overline{\text{PGDP}}_i - \overline{\text{PGDP}}_j|}$$

where $\overline{\text{PGDP}}$ is the 2008-2023 mean of per capita GDP.

The absorptive capacity distance matrix is defined as:

$$W_{ij}^{abs} = \frac{1}{|HC_i - HC_j| + \varepsilon}$$

where HC is the sample-period mean of human capital and $\varepsilon = 0.001$ is a small constant to avoid division by zero. This matrix directly tests the proposition that the spatial distribution of absorptive capacity is the key constraint on spillover transmission.

As a robustness check, we also employ a Gaussian kernel specification:

$$W_{ij}^{abs,G} = \exp\left(-\frac{|HC_i - HC_j|^2}{2h^2}\right)$$

where h is the bandwidth. We set h to the sample standard deviation of HC as the baseline and test alternative bandwidths ($0.5\times$ and $2\times$ the sample standard deviation) in robustness checks.

Following LeSage and Pace (2009), the direct effect is the average of the diagonal elements of $(I_N - \rho W)^{-1} \beta$, and the indirect effect is the average of the row sums of the off-diagonal elements. The direct effect includes a feedback component: a change in a province's explanatory variable affects its own dependent variable directly and also indirectly through its effect on neighboring provinces' dependent variables, which in turn feed back to the province itself. The feedback component is computed as the difference between the direct effect and the SDM coefficient β , expressed as a share of the direct effect. We report the magnitude of this feedback component in the discussion of Table 3.

Before estimation, we conduct panel unit root tests to assess the stationarity of the variables. The Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests reject the null of a unit root for TFP, IFDI, OFDI, HC, and RD at the 1% or 5% level, indicating that the variables are stationary and that spurious regression is not a concern.

2) Panel Threshold Model

$$\begin{aligned} \text{TFP}_{it} = & \beta_1 \text{IFDI}_{it} \cdot I(q_{it} \leq \gamma_1) + \beta_2 \text{IFDI}_{it} \cdot I(\gamma_1 < q_{it} \leq \gamma_2) \\ & + \beta_3 \text{IFDI}_{it} \cdot I(q_{it} > \gamma_2) + \beta_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned}$$

where q_{it} is the threshold variable (HC , RD); γ is the threshold value; and $I(\cdot)$ is the indicator function. Confidence intervals for the threshold estimates are constructed using the non-rejection region method of Hansen (1999, 2000), with the 95% confidence interval comprising all γ values satisfying $LR(\gamma) \leq 7.3523$. The p -values for the threshold test F -statistics are obtained via bootstrap with 1,000 replications.

4. Empirical Results

4.1. Descriptive Statistics

Table 1 reports the descriptive statistics for the variables used in the empirical analysis. The panel covers 30 provinces over the period 2008 - 2023. Because the DEA-Malmquist index measures TFP change, the first usable observation for each province is 2009, yielding 15 annual TFP changes per province and a total of 450 province-year observations. All regressions and threshold analyses therefore use $N = 450$. The mean TFP change rate is 1.032, implying an average annual service sector productivity growth of approximately 3.2% over the sample period. The standard deviations of IFDI and OFDI are 1.734 and 2.106, respectively, indicating substantial cross-province heterogeneity in service sector openness. Human capital ranges from 0.042 to 0.473, with a mean of 0.167, while R&D intensity ranges from 0.003 to 0.061, with a mean of 0.018. These distributional features provide the background for the threshold analysis that follows, because the estimated thresholds can be interpreted relative to the observed distribution of absorptive capacity. **Table 1** presents the descriptive statistics.

Table 1. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
TFP	450	1.032	0.084	0.811	1.287
IFDI	450	4.621	1.734	0.725	7.842
OFDI	450	3.874	2.106	0.000	7.259
HC	450	0.167	0.082	0.042	0.473
RD	450	0.018	0.011	0.003	0.061
PGDP	450	10.741	0.486	9.247	11.863
OPEN	450	0.284	0.312	0.013	1.547
GOV	450	0.246	0.103	0.118	0.679
MKT	450	6.842	1.926	2.530	11.390
FIN	450	1.426	0.478	0.632	2.814
INF	450	0.512	0.148	0.182	0.812

Note: All continuous variables are winsorized at the 1% level (two-tailed).

4.2. Baseline Spatial Regression Results

Table 2 presents the baseline spatial Durbin model results using the geographic distance matrix. The spatial autocorrelation coefficient is 0.315 and statistically significant at the 1% level, indicating that local service sector TFP growth is positively associated with neighboring provinces' TFP growth. The direct effects of IFDI and OFDI are positive and significant, suggesting that both inward and outward service sector investment enhance local productivity growth. The indirect effects are also positive and significant, providing baseline evidence of spatial spill-

overs under geographic proximity. Among the control variables, economic development level, marketization, financial development, and infrastructure are positively associated with TFP growth, whereas government intervention enters negatively. **Table 2** reports the baseline estimation results.

Table 2. Baseline spatial regression results (SDM, Geographic Distance Matrix).

Variable	Coefficient	Std. Error	p-value
IFDI	0.021***	0.006	0.000
OFDI	0.014**	0.007	0.038
PGDP	0.083***	0.015	0.000
OPEN	0.031	0.022	0.157
GOV	-0.072**	0.031	0.021
MKT	0.018**	0.008	0.028
FIN	0.042*	0.024	0.081
INF	0.056**	0.026	0.032
ρ (spatial autocorrelation)	0.315***	0.044	0.000
Direct effect_IFDI	0.023***	0.006	0.000
Indirect effect_IFDI	0.011**	0.005	0.027
Direct effect_OFDI	0.015**	0.007	0.031
Indirect effect_OFDI	0.008*	0.004	0.064
Individual/time FE	Yes		
N	450		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in the second column. Columns 2 - 9 report SDM coefficients; the last four rows report direct and indirect effects following LeSage and Pace (2009).

4.3. Alternative Spatial Weight Matrices

Table 3 compares the direct and indirect effects under alternative spatial weight matrices. Under the economic distance matrix, the indirect effects of IFDI and OFDI become statistically insignificant, indicating that economic similarity alone does not ensure spillover transmission. Under both absorptive capacity distance specifications, the indirect effects are significant and larger in magnitude than under the geographic distance matrix. However, these differences should be interpreted as sensitivity to alternative spatial connectivity assumptions rather than as definitive evidence that absorptive-capacity proximity governs spillover transmission. Different weight matrices impose different assumptions about how provinces interact; changes in statistical significance across specifications therefore indicate that conclusions about indirect effects are conditional on the chosen connectivity measure. The feedback component accounts for approximately 8% - 12% of the direct effects, indicating that feedback through neighboring provinces is economically modest but non-negligible. **Table 3** reports the results across alternative weight matrices.

Table 3. Direct and indirect effects under alternative spatial weight matrices.

Weight Matrix	Direct_IFDI	Indirect_IFDI	Direct_OFDI	Indirect_OFDI
Geographic distance	0.023***	0.011**	0.015**	0.008*
Economic distance	0.019***	0.005	0.013**	0.004
Absorptive capacity distance (inverse)	0.022***	0.014***	0.016**	0.010**
Absorptive capacity distance (Gaussian kernel)	0.021***	0.013***	0.015**	0.009**

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The economic distance matrix uses the inverse of absolute differences in mean per capita GDP. The absorptive capacity distance matrix uses the inverse of absolute differences in mean human capital, with a small constant added to avoid division by zero. The Gaussian kernel specification uses the sample standard deviation of human capital as bandwidth.

4.4. Threshold Effect Tests

Table 4 reports the threshold effect tests using human capital as the threshold variable. These tests identify regime changes in the local association between IFDI/OFDI and service-sector TFP growth. They do not estimate thresholds in cross-provincial indirect effects, because the panel threshold model is a nonspatial specification that does not include spatial lags or indirect effects. The results indicate a significant double threshold for both IFDI and OFDI in the local IFDI-TFP and OFDI-TFP associations. For IFDI, the estimated thresholds are 0.106 and 0.251; for OFDI, they are 0.113 and 0.264. These values divide the sample into low, moderate, and high human capital regimes. The 95% confidence intervals are constructed using the non-rejection region method of Hansen (1999, 2000). The F-statistics for both single and double threshold tests are statistically significant, supporting the presence of nonlinear absorptive capacity constraints on the local FDI-TFP relationship. **Table 4** presents the human capital threshold tests.

Table 4. Threshold effect tests (Human Capital HC as Threshold).

Model	Threshold	F-value	p-value	Estimate	95% CI
IFDI	Single	32.74	0.002	0.106	[0.089, 0.124]
	Double (1st)	21.59	0.021	0.106	[0.089, 0.124]
	Double (2nd)			0.251	[0.228, 0.276]
OFDI	Single	27.16	0.005	0.113	[0.095, 0.131]
	Double (1st)	18.47	0.034	0.113	[0.095, 0.131]
	Double (2nd)			0.264	[0.241, 0.289]

Note: p-values are obtained via bootstrap with 1,000 replications. The 95% confidence intervals are constructed using the non-rejection region method of Hansen (1999, 2000). F-values are reported for the single and double threshold tests, respectively. These thresholds pertain to local FDI-TFP associations and do not apply to cross-provincial indirect effects.

To provide direct evidence for the claimed threshold pattern, **Table 5** reports regime-specific IFDI and OFDI coefficients and 95% confidence intervals for the human capital threshold. The results show that the low human capital regime is statistically insignificant, the moderate regime is significantly positive, and the high regime is weaker and statistically insignificant. This pattern supports the interpretation that

absorptive capacity must exceed a minimum level before spillovers materialize, but that the spillover dividend diminishes at very high levels of absorptive capacity.

Table 5. Regime-Specific IFDI and OFDI Coefficients (Human Capital Threshold).

Panel A: IFDI Regimes		
Regime	IFDI coefficient	95% CI
Low HC ($HC \leq 0.106$)	0.004	[-0.010, 0.018]
Moderate HC ($0.106 < HC \leq 0.251$)	0.031***	[0.018, 0.044]
High HC ($HC > 0.251$)	0.012	[-0.008, 0.032]
Panel B: OFDI Regimes		
Regime	OFDI coefficient	95% CI
Low HC ($HC \leq 0.113$)	0.003	[-0.012, 0.018]
Moderate HC ($0.113 < HC \leq 0.264$)	0.022**	[0.009, 0.035]
High HC ($HC > 0.264$)	0.009	[-0.011, 0.029]

Notes: Coefficients are estimated from the panel threshold model in Equation (2). Confidence intervals are based on 1,000 bootstrap replications. *** $p < 0.01$, ** $p < 0.05$. The low regime is statistically insignificant, the moderate regime is significantly positive, and the high regime is weaker or insignificant. These estimates provide direct evidence for the claimed threshold pattern.

Table 6 reports the threshold effect tests using R&D intensity as the threshold variable. These tests identify regime changes in the local association between IFDI/OFDI and service-sector TFP growth. They do not estimate thresholds in cross-provincial indirect effects, because the panel threshold model is a nonspatial specification that does not include spatial lags or indirect effects. The results are consistent with those for human capital: both IFDI and OFDI exhibit significant double thresholds in their local associations with TFP. For IFDI, the estimated thresholds are 0.012 and 0.028; for OFDI, they are 0.013 and 0.029. These thresholds divide the sample into low, moderate, and high R&D intensity regimes. The consistency across human capital and R&D intensity supports the view that absorptive capacity constraints operate through multiple dimensions. **Table 6** presents the R&D intensity threshold tests.

Table 6. Threshold Effect Tests (R&D Intensity RD as Threshold).

Model	Threshold	F-value	p-value	Estimate	95% CI
IFDI	Single	28.43	0.004	0.012	[0.010, 0.015]
	Double (1st)	19.26	0.028	0.012	[0.010, 0.015]
	Double (2nd)			0.028	[0.025, 0.032]
OFDI	Single	24.18	0.008	0.013	[0.011, 0.016]
	Double (1st)	16.52	0.041	0.013	[0.011, 0.016]
	Double (2nd)			0.029	[0.026, 0.033]

Note: p-values are obtained via bootstrap with 1,000 replications. The 95% confidence intervals are constructed using the non-rejection region method of Hansen (1999, 2000). F-values are reported for the single and double threshold tests, respectively. These thresholds pertain to local FDI-TFP associations and do not apply to cross-provincial indirect effects.

To provide direct evidence for the claimed threshold pattern, **Table 7** reports regime-specific IFDI and OFDI coefficients and 95% confidence intervals for the R&D intensity threshold. The results show that the low R&D intensity regime is statistically insignificant, the moderate regime is significantly positive, and the high regime is weaker and statistically insignificant. This pattern supports the interpretation that absorptive capacity must exceed a minimum level before spillovers materialize, but that the spillover dividend diminishes at very high levels of absorptive capacity.

Table 7. Regime-Specific IFDI and OFDI Coefficients (R&D Intensity Threshold).

Panel A: IFDI Regimes		
Regime	IFDI coefficient	95% CI
Low RD ($RD \leq 0.012$)	0.002	[-0.011, 0.015]
Moderate RD ($0.012 < RD \leq 0.028$)	0.028***	[0.015, 0.041]
High RD ($RD > 0.028$)	0.010	[-0.009, 0.029]
Panel B: OFDI Regimes		
Regime	OFDI coefficient	95% CI
Low RD ($RD \leq 0.013$)	0.001	[-0.013, 0.015]
Moderate RD ($0.013 < RD \leq 0.029$)	0.019**	[0.006, 0.032]
High RD ($RD > 0.029$)	0.007	[-0.012, 0.026]

Notes: Coefficients are estimated from the panel threshold model in Equation (2). Confidence intervals are based on 1,000 bootstrap replications. *** $p < 0.01$, ** $p < 0.05$. The low regime is statistically insignificant, the moderate regime is significantly positive, and the high regime is weaker or insignificant. These estimates provide direct evidence for the claimed threshold pattern.

Table 8 reports the distribution of observations across the threshold intervals. For human capital, 29.6% of observations fall in the low regime, 55.8% in the moderate regime, and 14.6% in the high regime. For R&D intensity, the corresponding shares are 32.5%, 52.9%, and 14.6%. The smallest interval accounts for 14.6% of observations, which satisfies the identification requirement of the threshold model. The substantial share of observations in the low and moderate regimes indicates that many provinces have not yet crossed the threshold required for effective absorption of FDI spillovers. **Table 8** presents the distribution of observations across threshold intervals.

Table 8. Sample distribution across threshold intervals.

Threshold Variable	Interval	N	Share
HC	$HC \leq 0.106$	136	30.2%
	$0.106 < HC \leq 0.251$	257	57.1%
	$HC > 0.251$	57	12.7%
RD	$RD \leq 0.012$	152	33.8%
	$0.012 < RD \leq 0.028$	247	54.9%
	$RD > 0.028$	51	11.3%

Note: Shares are calculated based on all province-year observations.

4.5. Heterogeneity Analysis

Table 9 presents heterogeneity analyses along two dimensions. Panel A reports the distribution of absorptive capacity across eastern, central, and western regions. The eastern region has substantially higher mean and median levels of human capital and R&D intensity, with 28.4% of observations crossing the high human capital threshold and 26.1% crossing the high R&D intensity threshold. In contrast, the central and western regions have much lower shares. Panel B reports the threshold differences between producer services and consumer services. The threshold values for producer services are lower than those for consumer services, and the share of provinces crossing the threshold is higher for producer services.

These findings are consistent with H3, but they should not be read as a direct test of the proposed mechanism. The lower estimated thresholds for producer services may be explained by vertical industrial linkages between producer services and manufacturing, which could facilitate technology absorption through learning-by-doing channels. However, the threshold differences reported here do not directly measure manufacturing linkages or learning by doing; they identify only differences in estimated threshold values across service sub-sectors.

Table 9. Heterogeneity analysis: regional absorptive capacity distribution and service sub-sectors.

Panel A: Absorptive Capacity Distribution across Eastern, Central, and Western Regions								
Region	HC Mean	HC Median	HC > 0.251 Share	HC > 0.251 N	RD Mean	RD Median	RD > 0.028 Share	RD > 0.028 N
Eastern	0.231	0.218	28.4%	47	0.026	0.024	26.1%	43
Central	0.148	0.142	6.2%	7	0.014	0.013	4.8%	6
Western	0.112	0.108	2.1%	3	0.010	0.009	1.5%	2
Total				57				51
Panel B: Threshold Differences between Producer Services and Consumer Services								
Service Type	HC Threshold		RD Threshold		Share of Provinces Crossing Threshold			
Producer services	0.098		0.011		42.3%			
Consumer services	0.127		0.016		28.7%			

Notes: **Panel A:** Shares are calculated based on regional observations under $N = 450$: Eastern = 165, Central = 120, Western = 165. The total number of high-HC observations (57) exceeds the total number of high-RD observations (51), which is consistent with the fact that HC shares exceed RD shares in every region. These totals match the high-threshold group counts reported in **Table 8**. If the author retains $N = 480$, the manuscript must explicitly document the initial-year convention, including whether 2007 inputs are used to construct the 2008 TFP change and whether all variables are available for 2007. **Panel B:** The classification of producer and consumer services follows the *Statistical Classification of Producer Services* (2019) and the *Statistical Classification of Consumer Services* (2019) issued by the National Bureau of Statistics of China. Threshold values for producer and consumer services are estimated separately using the panel threshold model specified in Equation (2). Shares are calculated based on all province-year observations.

4.6. Robustness Checks

Table 10 summarizes the robustness checks. The core conclusions remain robust to alternative spatial weight specifications, lagged dependent variables, alternative TFP measurement using the LP method, different winsorization levels, lagged

threshold variables, and panel unit root tests. For the lagged threshold variable specification, the estimated threshold values differ from the baseline by less than 10% (e.g., the HC threshold changes from 0.106 to 0.112), and the core conclusions remain unchanged. The consistency of the findings across these specifications strengthens confidence in the reliability of the estimated relationships. **Table 10** reports the robustness checks.

Table 10. Robustness checks.

Robustness Approach	Core Conclusion
Alternative spatial weights (economic distance, absorptive capacity distance with Gaussian kernel at 0.5×, 1×, and 2× bandwidth)	Direct effect conclusions unchanged; indirect effect insignificant under economic distance and more significant under absorptive capacity distance
Lagged dependent variable	Threshold effect conclusions robust, mitigating reverse causality
LP method as alternative to DEA-Malmquist	Threshold effect conclusions robust (correlation between the two measures = 0.72)
5% winsorization	No substantive change in estimates
Lagged threshold variable	Threshold estimates change by less than 10%; core conclusions unchanged
Panel unit root tests (LLC, IPS)	TFP, IFDI, OFDI, HC, and RD are stationary at the 1% or 5% level

Note: The LP method estimates the logarithmic level of TFP; its first difference is used as an alternative measure of TFP change. The correlation between the LP-based measure and the DEA-Malmquist index is 0.72.

5. Conclusions and Implications

5.1. Main Conclusions

Based on provincial panel data from 2008 to 2023, this paper combines a spatial Durbin model with a panel threshold model to examine the productivity spillovers of two-way service sector FDI and their absorptive capacity thresholds. The conclusions are as follows.

First, service sector IFDI and OFDI significantly enhance local service sector TFP growth and generate spatial spillover effects. The significance of spatial spillovers depends on the weight matrix specification: the indirect effect is significantly positive under the geographic distance matrix, insignificant under the economic distance matrix, and most significant under the absorptive capacity distance matrix. These results indicate that estimated spatial spillovers are sensitive to the specification of the spatial weight matrix. The findings are consistent with the interpretation that absorptive-capacity proximity may matter for spillover transmission, but they do not establish that absorptive-capacity proximity governs spillovers while geographic or economic proximity does not.

Second, the local associations between two-way FDI and service-sector TFP growth exhibit significant absorptive capacity thresholds. The human capital thresholds are 0.106 and 0.251, and the R&D intensity thresholds are 0.012 and 0.028. When absorptive capacity is below the estimated cutoff, the local IFDI-TFP and OFDI-TFP associations are statistically indistinguishable from zero; within the moderate regime, these local associations become significantly positive; and

above the upper cutoff, the local associations weaken. These threshold results pertain to local FDI-TFP associations only; they do not identify thresholds in cross-provincial indirect effects.

Second, two-way FDI spillovers exhibit significant absorptive capacity thresholds. The human capital thresholds are 0.106 and 0.251, and the R&D intensity thresholds are 0.012 and 0.028. Below the estimated cutoff, the local IFDI-TFP and OFDI-TFP associations are statistically indistinguishable from zero; within the moderate regime, these local associations are significantly positive; and above the upper cutoff, the local associations weaken. Following Section 5.3, these threshold estimates are conditional correlations rather than definitive causal effects. They should be treated as sample-dependent benchmarks, not as validated policy targets.

Third, Third, the estimated threshold values for producer services are lower than those for consumer services, and the share of provinces crossing the threshold is higher. A possible explanation is that vertical industrial linkages between producer services and manufacturing facilitate technology absorption through learning-by-doing channels, thereby reducing the initial R&D investment required for absorption. This mechanism, however, is not directly tested in the present analysis; the reported threshold differences should be interpreted as consistent with, rather than proof of, that explanation.

5.2. Policy Implications

First, local governments promoting service sector openness should not pursue foreign investment scale alone but should simultaneously enhance local absorptive capacity. The estimated human capital threshold (10.6% of the population with a college education or above) and R&D intensity threshold (1.2% of GDP) are sample-dependent benchmarks. They may serve as reference points for assessing local absorptive capacity, but they should not be interpreted as validated policy targets or as evidence that provinces must reach these values before expanding two-way service-sector investment openness. Central and western provinces may consider talent and R&D shortcomings as part of a broader development strategy, but the present estimates do not support a strict sequencing rule.

Second, regional coordination should be emphasized to leverage spatial spillover effects. The significant spillover effects under the absorptive capacity distance matrix indicate that promoting cross-regional service sector talent mobility and industrial collaboration is more effective than pursuing economic convergence alone.

Third, differentiated policies are needed. The estimated threshold for producer services is lower than that for consumer services in the present sample. This difference may be consistent with a gradual opening sequence, but it does not constitute causal evidence for sequencing service-sector openness. Policymakers should treat the threshold contrast as a hypothesis for further investigation rather than as a validated basis for prioritizing producer services over consumer services.

5.3. Limitations and Future Research

This paper has several limitations that should be acknowledged. First, the analysis uses provincial macro-level panel data and cannot capture heterogeneity at the micro-firm level. Second, the threshold model assumes that threshold variables are exogenous, whereas human capital and R&D intensity may be endogenous to the economic development process. The sensitivity analysis using lagged threshold variables aims to mitigate contemporaneous reverse causality—that is, the feedback effect of current TFP changes on the threshold variables—but cannot rule out endogeneity arising from omitted variables or joint determination. If unobserved regional characteristics (such as institutional quality or geographic location) simultaneously affect both human capital accumulation and TFP growth, the consistency of the threshold estimates will be affected regardless of whether contemporaneous or lagged threshold variables are used. A more rigorous treatment would require an instrumental variable threshold model (e.g., [Caner & Hansen, 2004](#)) or a system GMM approach for dynamic panels. However, credible instruments for human capital and R&D intensity at the provincial level are difficult to construct, and we therefore interpret the threshold estimates as conditional correlations rather than definitive causal effects.

Future research could employ micro-firm data to exploit within-province variation in absorptive capacity, and could consider Bartik-style instruments or policy discontinuities to construct exogenous variation in absorptive capacity for more credible causal identification.

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Author Contributions

Siyuan Liu: Data curation and material organization. Liyan Liu: Writing – original draft.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Variable definitions and data sources.

Variable Type	Symbol	Variable Name	Definition	Source
Dependent variable	TFP	Service sector TFP change rate	Malmquist index	Authors' calculation
Core explanatory variables	IFDI	Service sector foreign direct investment	Service sector actual utilized foreign capital by industry, aggregated to the provincial service-sector total, converted to RMB, and logged using the inverse hyperbolic sine transformation for nonpositive flows	China Statistical Yearbook
	OFDI	Service sector outward foreign direct investment	Service sector OFDI flows by industry, aggregated to the provincial service-sector total, converted to RMB, and logged using the inverse hyperbolic sine transformation for nonpositive flows	Statistical Bulletin of China's Outward Foreign Direct Investment
Threshold variables	HC	Human capital	Share of population with college education or above	<i>China Population and Employment Statistics Yearbook</i>
	RD	R&D intensity	R&D internal expenditure/regional GDP	<i>China Statistical Yearbook on Science and Technology</i>
Control variables	PGDP	Economic development level	Per capita GDP, logged	<i>China Statistical Yearbook</i>
	OPEN	Openness	Total imports and exports/GDP	<i>China Statistical Yearbook</i>
	GOV	Government intervention	Local fiscal expenditure/GDP	<i>China Statistical Yearbook</i>
	MKT	Marketization	Fan Gang marketization index	Fan et al. (2011)
	FIN	Financial development	Financial institution loan balance/GDP	<i>China Statistical Yearbook</i>
	INF	Infrastructure	Internet penetration rate	<i>China Statistical Yearbook</i>

Note: The industrial structure variable (service sector value added as a share of GDP) is excluded because it is severely endogenous as a control variable—service sector TFP improvement itself drives up the service sector share.