

Digital Economy Effects in Smart Logistics Growth: Spatial Patterns and Financial Thresholds

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Abstract

The relationship between the digital economy and smart logistics growth is a central issue in the modernization of circulation systems, yet existing studies mostly characterize the linkage with level indicators and pay insufficient attention to growth-level conditionality and spatial structure. Using a balanced panel of 30 Chinese provinces over 2015–2024, this paper employs a spatial Durbin model and a panel threshold model to examine the conditional association between the two. The findings show that robust evidence for a local direct association is lacking: the effect is insignificant under the economic distance framework and only marginally positive under geographic adjacency. The most robust finding is a negative spatial spillover—the digital economy of neighboring provinces is negatively associated with local growth—a pattern that persists under alternative weight matrices, extended windows, exclusion of the pandemic years, and the inclusion of spatial controls. A threshold-type conditional association exists between financial deepening and effect release, but it passes the 5% test only under the three-year non-spatial specification and becomes insignificant once spatial structure is incorporated; it should therefore be positioned as an exploratory finding. The mechanism exploration does not support the network-density channel, and the instrumental-variable diagnostics indicate that the current data can hardly support strong causal identification. These results suggest that the logistics growth effects of the digital economy operate mainly through the spatial dimension, and policy design should attach importance to transformation conditions and regional coordination.

1 Introduction

1.1 Research background and questions

The rapid expansion of the digital economy is reshaping the underlying logic of industrial organization in China. Telecommunication infrastructure has become increasingly pervasive, the software and information service sector continues to expand, and digital technologies are now deeply embedded in production, circulation, and consumption. The contribution of the digital economy to economic growth keeps rising, and measurement studies indicate that its scale and structure are still evolving [1][2]. Logistics connects production and consumption; the share of total social logistics costs in GDP has remained high for a long time, leaving substantial room for cost reduction and efficiency gains, so logistics is widely regarded as the most promising application scenario of the digital economy. Practices such as automated sorting, intelligent warehousing, route optimization, and supply-chain coordination have been implemented one after another, and smart logistics has thus moved to the core of the policy agenda. Since the 14th Five-Year Plan period, policy deployments at all levels—from new infrastructure construction to the modern circulation system—have listed smart logistics as a priority direction. These deployments implicitly assume that digital inputs can automatically translate into logistics efficiency and growth. However, this assumption lacks rigorous empirical testing, and a clear gap persists between widely circulated judgments in policy discussions and academic evidence—a gap that is particularly pronounced in the field of smart logistics. Does the expansion of the digital economy really generate sustained growth in smart logistics? Is the effect stable? To what extent does it depend on regional conditions and the supporting environment? These questions remain open. The answers bear directly on where digital logistics policies should direct resources and how their effects are evaluated, and on whether development opportunities are allocated fairly across regions.

1.2 Literature review

Existing studies roughly follow two threads. The first thread concerns the macroeconomic performance of the digital economy. Research finds that the digital economy exerts positive effects on total factor productivity, high-quality development, and green transformation, and the mechanisms through which the internet raises manufacturing productivity have been examined in detail [3][4]. These studies mostly adopt level or efficiency indicators and can

hardly answer questions at the growth level, yet growth is precisely the dimension that policy evaluation cares about most. The second thread focuses on the logistics industry itself, examining the impact of digital technologies on logistics carbon-emission efficiency and the green logistics system [5][6]. The conclusions are predominantly positive but likewise remain largely at the level of correlation and levels. More importantly, few studies incorporate the spatial dimension into the analytical framework. The effects of the digital economy may spill over through interregional factor flows and market competition; ignoring spatial association not only affects estimation consistency but also obscures the policy implications. The direction of spatial spillover determines whether regional policy should stress coordination or competition, and whether the growth of pioneering regions comes at the expense of their neighbors. In addition, the digital economy may require specific supporting conditions to work. The degree of financial deepening is closely related to corporate financing capacity, and this conditionality has not been adequately discussed in the existing literature [7][8]; most studies implicitly assume the effect is homogeneous and unconditional. These gaps constitute the entry point of this paper.

Research on the relationship between the digital economy and logistics development has become increasingly rich. Some studies construct digital economy indices at the provincial or city level and find that the digital economy promotes green total factor productivity, energy efficiency, and low-carbon development; improvements in urban sustainable development and carbon efficiency are also supported by evidence [9][10]. These conclusions provide indirect evidence for understanding how the digital economy affects logistics. Other studies focus directly on logistics, finding that digital economy development can raise the carbon-emission efficiency of the logistics industry and promote the building of regional green logistics systems [5][6]. Digital technologies also affect industry performance through business model innovation and organizational change [11]. Domestic studies have likewise accumulated substantial evidence that the digital economy promotes high-quality development [1], and the mechanisms through which the internet raises manufacturing productivity have been carefully documented [3]. It should be noted, however, that most of these studies use level or efficiency indicators as the explained variable, reflecting the comovement between the digital economy and logistics levels rather than growth-level associations. Level comovement and growth driving are substantively different: the former may arise from common trends, whereas only the latter corresponds to genuine input–output transformation. Re-examining the relationship in growth terms therefore has independent value and provides a more direct basis for policy evaluation.

After shifting the focus from levels to growth rates, the effect of the digital economy is far from automatic. Existing findings on the internet's impact on productivity are not entirely consistent [4]: some studies find significant promotion, others find limited effects. This divergence itself suggests that the growth effect of digital technologies may be conditional rather than unconditional. Mechanically, the diffusion of digital technology involves an absorption process; the upfront costs of equipment procurement, system integration, and staff training erode short-run returns. Logistics growth also depends on structural factors such as demand expansion, infrastructure, and market competition; digital technology is only one link, and its marginal contribution may be masked by the movements of other factors or absorbed by industry cycles. Taken together, these considerations point to one judgment: growth-level associations may be unstable, and their manifestation depends on specific conditions. Spatial transmission and supporting conditions are the two most noteworthy dimensions—the former addresses where the effect is transmitted, and the latter addresses under what environment it materializes; their relative importance must be judged from the data. Accordingly, the analytical framework of this paper consists of three links—direct association, spatial pattern, and threshold conditions—which correspond to three hypotheses and three model specifications, forming the basic thread of the subsequent chapters.

1.3 Research approach and contributions

Building on the literature review above, existing studies have laid important foundations in three areas—the digital economy and logistics, spatial spillovers, and threshold mechanisms—but room for advancement remains. First, most studies characterize the explained variable with level or efficiency indicators, and growth-level associations lack careful testing, although growth is the core object of policy evaluation. Second, spatial analysis concentrates on macroeconomic variables; research on the spatial structure of logistics growth is relatively limited, and the influence of spatial weight choices on the conclusions has not been fully discussed. Third, the role of financial conditions is mostly handled through moderation or heterogeneity; threshold-type conditional features have not been fully identified, and the location of critical points is seldom explicitly estimated. Accordingly, this paper takes the growth rate of the composite smart logistics level as the research object and uses panel data of 30 provinces over 2015–2024. The analysis covers three questions in turn: the direct association between the digital economy and smart logistics growth, the spatial transmission pattern, and the role of financial conditions. It should be noted that, constrained by instrument quality and data structure, this paper does not claim strong causal identification; the research goal is positioned as a rigorous characterization of conditional associations and spatial patterns. These three threads correspond to the three analytical dimensions of this paper—the choice of the growth-rate caliber, the identification of spatial transmission, and the threshold test of financial conditions. The theoretical analysis and model specification below proceed along these dimensions.

2 Theoretical framework and hypotheses

2.1 Local effects of the digital economy and their conditionality

Once the focus shifts from levels to growth rates, the effect of the digital economy is no longer self-evident and must be examined from two perspectives: technology diffusion and industry operation. On one hand, the diffusion of digital technology involves an absorption process. Firms need time to convert digital inputs into organizational capabilities and business processes; the upfront costs of equipment procurement, system integration, and staff training erode short-run returns, so the growth effect may not appear immediately. The time lag of technology adoption makes it difficult to establish a direct correspondence between current inputs and current outputs, which is especially salient in asset-heavy industries such as logistics. On the other hand, logistics growth also depends on structural factors such as demand expansion, infrastructure, and market competition; digital technology is only one link, and its marginal contribution may be masked by the movements of other factors. Existing findings on the internet's impact on productivity are not entirely consistent [4], which itself suggests that the growth effect of digital technologies may be conditional. Accordingly, Hypothesis 1 is proposed: the local direct association between the digital economy and smart logistics growth is statistically unstable, and its manifestation may depend on spatial channels and supporting conditions. This hypothesis is the starting point of the whole analysis; the subsequent spatial decomposition and threshold tests are organized around it, and it is also the key to the dialogue between this paper and the existing level-based research.

2.2 Two competing hypotheses on spatial spillovers

The spatial effect of the digital economy is one of the core dimensions of this paper. Existing evidence indicates that the impact of the digital economy on total factor productivity exhibits pronounced spatial spillover: city-level studies document cross-regional transmission [12], industry-level studies confirm the spatial association of green total factor productivity in manufacturing [13], and the spatially non-linear effects of digital finance are verified in smart-city samples [14][15]. Theoretically, this spillover may take two opposite directions. The diffusion view holds that the digital technologies, managerial experience, and supply-chain networks of pioneering regions extend outward along geographic proximity, jointly raising the logistics organization efficiency of neighboring areas, so the indirect effect is positive. The siphoning view holds that digital resources tend to concentrate in leading regions—talent, capital, and

data traffic converge toward digital economy hubs—so neighboring regions face factor loss and market diversion, and the indirect effect is negative. Both effects may coexist, and the net effect depends on how spatial association is measured and on the stage of regional development, as well as on the organizational features of logistics networks. Logistics networks are inherently cross-regional. Geographic proximity is the most direct carrier of technology spillover and factor flow, so the spatial structure under adjacency should be clearer than that under economic similarity. Accordingly, Hypothesis 2 is proposed: the impact of the digital economy on smart logistics growth may exhibit a pattern in which local and neighboring associations point in opposite directions, and this pattern is more pronounced under the geographic-adjacency channel.

2.3 Threshold conditions of financial deepening

Whether the digital dividend can be released depends largely on the supporting financial conditions. The promoting role of financial development for economic growth has long been supported by extensive evidence [16]. The financial system mobilizes savings, screens projects, and diversifies risks, thereby lowering the threshold for corporate investment—a role that is especially prominent in transition economies. Converting digital technology into logistics productivity requires equipment procurement, system upgrading, and talent recruitment, all of which depend on the availability of external financing. Logistics firms are mostly small and medium-sized and are more sensitive to the financial environment. When financial deepening is low, even if firms identify digital opportunities, they may fail to implement them under financing constraints, and the marginal effect of the digital economy is close to zero. Once financial deepening crosses a certain level, financing constraints ease and digital technology can translate into real growth momentum. Existing studies have documented threshold features of the digital economy in green growth and green innovation [7][8], and the impact of digital finance on green total factor productivity has been shown to be non-linear with spatial thresholds [15]. Together these findings suggest that financial deepening may constitute the critical condition for releasing the effects of the digital economy. Whether this condition manifests stably depends on whether it passes tests under more general settings. Accordingly, Hypothesis 3 is proposed: under non-spatial conditions, there exists a threshold-type association between financial deepening and the release of digital economy effects, with the positive association strengthening beyond the threshold. However, this association may be sensitive to spatial structure and is therefore treated as an exploratory finding.

The three hypotheses are interlocking and together constitute a complete answer to the research question. Hypothesis 1 points to the test of the local direct association: if the association is unstable, other channels must be sought. Hypothesis 2 points to the identification of the spatial pattern, answering through which channel the effect is transmitted. Hypothesis 3 points to the identification of threshold conditions, answering under what environment the effect materializes. The three proceed step by step, and none can be dispensed with. Logically, the test of the direct association motivates the spatial analysis, and the conclusions of the spatial analysis provide the background for the threshold test; the threshold findings, in turn, provide a condition-level explanation for the instability of the direct association, closing the loop. It should be noted that the hypotheses are not prior assumptions but the result of converging theoretical reasoning and empirical facts. The testing process matters as much as the conclusions, and the strength of evidential support may differ across hypotheses. The following sections present the research design, empirical evidence, and policy implications, testing each hypothesis in turn. It should be emphasized that the estimation strategy of this paper centers on characterizing conditional associations, combined with limited identification diagnostics, striving to give prudent and clear judgments within the limits that the strength of evidence allows. This stance respects data quality and anticipates common skepticism in peer review.

3 Research design

3.1 Model specification

To examine local effects and spatial spillovers simultaneously, this paper adopts the spatial Durbin model (SDM) as the baseline specification. The SDM allows the spatially lagged explanatory variables to enter the equation and yields direct and indirect effects through the partial-derivative decomposition [17][18]. It thus places local impacts and cross-regional transmission in a unified framework and avoids misreading spillovers with simple spatial regressions. The model is estimated with two-way (province and year) fixed effects to control for time-invariant provincial heterogeneity and common national shocks; two-way fixed effects also mitigate the omitted-variable bias on the core parameters. The spatially lagged explanatory variables cover the core explanatory variable and the controls. The adequacy of the SDM relative to the spatial lag and spatial error models is judged by Wald and LR tests: if the spatially lagged explanatory variables are jointly significant, the SDM cannot degenerate into simpler forms. The distinction between direct and indirect effects is the core advantage of the SDM over conventional panel models and the basis for identifying the spatial pattern in this paper. The model is specified as in Eq. (1).

$$growth_{it} = \rho \sum_j w_{ij} growth_{jt} + \beta X_{it} + \theta \sum_j w_{ij} X_{jt} + \gamma Z_{it} + \delta \sum_j w_{ij} Z_{jt} + \mu_i + \nu_t + \epsilon_{it}$$

1

where $growth_{it}$ denotes the growth rate of the composite smart logistics level of province i in year t , X the digital economy level, Z the vector of control variables, and W the row-standardized spatial weight matrix; μ and ν are province and year fixed effects, respectively, and ϵ is the idiosyncratic error term.

Identification of spatial effects depends on the specification of the spatial weight matrix. This paper constructs two weight matrices for mutual corroboration. The economic distance matrix defines weights as the reciprocal of the absolute difference in per-capita GDP between provinces, capturing the strength of association between regions with similar development levels. Regions with similar economic structures face similar digitalization demands and competitive landscapes and are more likely to substitute for one another's markets. The Rook adjacency matrix defines weights by shared boundaries, capturing association between geographically proximate regions. Factor flows, technology spillover, and market substitution all occur more easily between adjacent areas, and geographic distance is the most natural metric of spatial interaction. Both matrices are row-standardized to ensure comparability of the weight structure and direct interpretation of the coefficients. The economic distance matrix captures mutual influence along the economic-similarity dimension, and the adjacency matrix captures the geographic-proximity dimension; their comparison helps identify the channel through which the spatial effects of the digital economy operate. If effects are transmitted mainly through geographic proximity, a clearer spatial structure should emerge under the adjacency matrix, while results under the economic distance matrix should be relatively blurred. This comparison itself constitutes a test of the transmission channel and reduces the contingency that may arise from a single weight specification, grounding spatial inference on a more solid basis.

To examine the conditional role of financial deepening, this paper further adopts a panel threshold model with financial deepening as the threshold variable to test whether the coefficient of the digital economy undergoes structural shifts. The threshold model allows coefficients to differ across regimes, with regime boundaries determined endogenously by the data. The number and significance of thresholds are tested via Bootstrap [19], avoiding the subjectivity of manual grouping and improving on simple mean- or median-based splits. Considering that the threshold mechanism is a long-run structural feature, the threshold test uses the three-year growth rate as the explained variable and also reports the two-year specification for comparison, so as to observe the time-dimension differences of financial conditions. Threshold regression searches for the threshold by minimizing the residual sum of squares and constructs a likelihood-ratio statistic for the confidence interval of the threshold estimate. Human capital stock is also included in the threshold tests to examine whether the threshold mechanism is finance-specific. Since the threshold model excludes spatial structure, the robustness checks further examine the sensitivity of the threshold findings to spatial settings. The

estimation strategy thus proceeds in three steps—testing the direct association, decomposing spatial effects, and identifying threshold conditions—corresponding one-to-one to the three hypotheses. The model is specified as in Eq. (2).

$$growth_{\{3yr,it\}} = \beta_1 X_{\{it\}} I(fin_{\{it\}} \leq \gamma) + \beta_2 X_{\{it\}} I(fin_{\{it\}} > \gamma) + \lambda Z_{\{it\}} + \mu_i + \nu_t + \epsilon_{\{it\}}$$

2

where $fin_{\{it\}}$ is the level of financial deepening, γ is the threshold estimate, and $I(\cdot)$ is an indicator function; β_1 and β_2 are the coefficients of the low- and high-finance regimes, respectively.

3.2 Variables

The explained variable is the growth rate of the composite smart logistics level, constructed consistently with the indicator system described above. The composite smart logistics level is synthesized by entropy weighting from five dimensions and twenty-four indicators covering logistics infrastructure, informatization, service capacity, and operational efficiency (Appendix Table A1). The indicators include scale measures such as freight volume and turnover as well as efficiency measures such as unit logistics cost and timeliness, striking a balance between scale and efficiency to avoid measurement bias from a single dimension and to make cross-province comparison more robust. Growth rates are computed year over year; the sample covers 270 observations over 2016–2024, reflecting short-run changes in smart logistics. Considering the long construction cycle of smart logistics—digital investment often takes years from implementation to output—this paper also constructs a three-year rolling growth rate, covering 210 observations over 2018–2024, to identify medium- and long-run structural features. The contrast between the two calibers helps distinguish short-run fluctuations from long-run structure and provides time-dimension information for threshold identification. This design allows more credible distinctions between short-term noise and long-term trends, avoids misreading transitory disturbances as structural regularities, and echoes the earlier discussion of technology-absorption lags.

The core explanatory variable is the digital economy level, synthesized from three dimensions following existing measurement studies [1][2]: the share of telecommunication business volume in GDP, the share of software business revenue in GDP, and the number of websites per hundred enterprises, combined by entropy weighting. The three dimensions reflect the penetration of digital infrastructure, the output scale of the digital industry, and the penetration of enterprise digital applications, covering both the supply and demand sides. Control variables are the urbanization rate and the degree of openness, both entering at their initial-period values to reduce reverse interference from contemporaneous changes within the growth window. Higher urbanization concentrates logistics demand and strengthens the scale effects of infrastructure; openness reflects foreign-trade activity, and larger import–export volumes impose higher requirements on logistics efficiency and service capacity. The threshold variable is the level of financial deepening, measured by the ratio of RMB loan balances of financial institutions to GDP, with a sample mean of 1.666 and pronounced cross-province variation, providing sufficient variation for threshold identification. Human capital stock is included as a comparison threshold variable. The instruments are terrain ruggedness and the 1990 historical value of post and telecommunications business: the former reflects the natural cost of building digital infrastructure, and the latter reflects the region’s historical foundation of digitalization. Both correlate with the current digital economy level and have no direct link with smart logistics growth [20], making them typical supply-side instruments.

3.3 Data and descriptive statistics

This paper uses a balanced panel of 30 Chinese provinces over 2015–2024; Tibet is excluded due to data unavailability. The raw data mainly come from statistical yearbooks and industry statistics over the years, with consistent variable

calibers within the sample period. The construction of the explained variable, core explanatory variable, controls, threshold variable, and instruments is as described above. Table 1 reports the descriptive statistics of the main variables, and Table 2 reports the correlation matrix. Within the sample period, the mean of the smart logistics growth rate is 0.033 with a standard deviation of 0.066, indicating considerable variation in growth across provinces. The digital economy level averages 0.150, with a clear gap between maximum and minimum, showing unbalanced digital development across regions. Financial deepening averages 1.666, and its variation supports threshold identification. The means of urbanization and openness are 64.06 and 23.695, respectively, and human capital stock averages 8.873. The correlation matrix shows a simple correlation of 0.136 between the digital economy and the smart logistics growth rate—positive but modest—suggesting that the relationship may not be simple linear driving, echoing the regression results below. It should be noted that the sample period spans the COVID-19 phase of 2020–2022, during which logistics operations were visibly disturbed; the robustness checks address the pandemic years specifically.

Table 1
Descriptive statistics of main variables

Variable	Mean	Std. Dev.	Min	Max
growth	0.033	0.066	-0.258	0.281
X	0.150	0.112	0.015	0.531
M	6.911	1.597	2.731	10.720
urban	64.060	10.250	44.640	89.850
open	23.695	21.637	0.714	98.720
finance	1.666	0.403	0.873	2.759
humancap	8.873	0.819	7.441	11.477
terrain	1.030	1.050	0.004	4.326
post1990	1.167	0.533	0.222	2.763
Note: The sample is the growth-rate estimation sample (2016–2024).				

Table 2
Correlation matrix of main variables

Variable	growth	X	M	urban	open	finance	humancap
growth	1.000	0.136	0.207	0.181	0.180	0.059	0.101
X	0.136	1.000	0.183	0.273	0.166	0.307	0.296
M	0.207	0.183	1.000	0.722	0.728	0.216	0.609
urban	0.181	0.273	0.722	1.000	0.717	0.482	0.816
open	0.180	0.166	0.728	0.717	1.000	0.328	0.518
finance	0.059	0.307	0.216	0.482	0.328	1.000	0.266
humancap	0.101	0.296	0.609	0.816	0.518	0.266	1.000
Note: Correlations are computed on the growth-rate estimation sample (2016–2024).							

4 Empirical results and analysis

4.1 Baseline regression

Table 3 reports the SDM estimates under the economic distance matrix. After controlling for province and year fixed effects, the coefficient of the digital economy on the smart logistics growth rate is about 0.12, with a p-value near 0.3—far above conventional significance levels—indicating no identifiable association between the digital economy level and differences in smart logistics growth across provinces with similar economic development. The effect decomposition further shows a direct effect of about 0.11, an indirect effect of about – 0.26, and a total effect of about – 0.15, none of which passes significance tests. From either the local or the spillover perspective, no identifiable growth association exists under the economic distance channel. The spatial autocorrelation coefficient of the explained variable is about 0.32, marginally significant only at the 10% level, and the Wald test cannot reject the null that the spatially lagged explanatory variables are jointly zero; the model as a whole is closer to a reduced specification without spatial structure. These results should be interpreted with nuance: they indicate the absence of significant statistical evidence under the economic distance association, not a negation of the digital economy’s role. Whether local effects materialize still requires joint judgment with other spatial settings and conditional factors; the null results under the economic distance channel provide the backdrop for the subsequent geographic-adjacency test.

Table 3
SDM estimates under the economic distance matrix

Variable	Estimate
$\rho / W \cdot \text{growth}$	0.315* (0.189)
X	0.120 (0.116)
urban	0.006 (0.007)
open	-0.000529 (0.001)
W·X	-0.232 (0.184)
W·urban	-0.012 (0.011)
W·open	-0.000696 (0.002)
Wald test (joint insignificance of W·X, W·urban, W·open)	F = 0.963, p = 0.424
LR test (SDM vs SAR)	1.778, p = 0.620
LR test (SDM vs SEM, approx.)	1.467, p = 0.690
Observations	270
R ²	0.189
Fixed effects (province/year)	Yes/Yes
Note: Standard errors in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Dependent variable: growth; weight matrix: row-standardized economic distance matrix; urban and open enter at their initial-period values.	

4.2 Re-examination under the adjacency matrix

The null results under the economic distance matrix motivate this paper to turn to the geographic-proximity channel. Table 4 reports the estimates under the Rook adjacency matrix. With the weight matrix replaced, the coefficient of the digital economy is about 0.25, significantly positive at the 10% level, suggesting a positive association between the digital economy level of geographically adjacent provinces and local smart logistics growth. The change of weights

clearly alters the conclusion, indicating that the channel of spatial association is more likely geographic proximity than economic similarity. Specification tests support this choice: the Wald test yields $p = 0.005$, and the LR tests show that the SDM significantly outperforms the spatial lag and spatial error models, meaning the spatially lagged explanatory variables should not be dropped and ruling out model degeneration. Notably, the spatial autoregressive coefficient of the explained variable is insignificant, whereas the spatially lagged explanatory variables have clear explanatory power: the spatial lag of neighboring provinces' digital economy is significantly negative at the 10% level, the spatial lag of neighboring urbanization is negative, and the spatial lag of neighboring openness is significantly negative at the 1% level. The spatial association of provincial smart logistics growth operates mainly not through self-reinforcement of growth itself but through the cross-regional influence of the explanatory variables—the spatial effect of the digital economy is a typical explanatory-variable spillover rather than endogenous spatial dependence of the outcome.

Table 4
SDM estimates and specification tests under the Rook adjacency matrix

Variable	Estimate
ρ / $W \cdot \text{growth}$	-0.062 (0.165; $p = 0.708$)
X	0.253* (0.133; $p = 0.057$)
urban	0.010 (0.006; $p = 0.105$)
open	-0.001 (0.001; $p = 0.168$)
$W \cdot X$	-0.341* (0.206; $p = 0.097$)
$W \cdot \text{urban}$	-0.015* (0.008; $p = 0.073$)
$W \cdot \text{open}$	-0.006*** (0.002; $p = 0.002$)
Wald test (joint insignificance of $W \cdot X$, $W \cdot \text{urban}$, $W \cdot \text{open}$)	12.796, $p = 0.005$
LR test (SDM vs SAR)	11.350, $p = 0.010$
LR test (SDM vs SEM, approx.)	11.354, $p = 0.010$
Observations	270
R^2	0.209
Fixed effects (province/year)	Yes/Yes
Note: Standard errors and p-values in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Dependent variable: growth; weight matrix: row-standardized Rook adjacency matrix; urban and open enter at their initial-period values.	

4.3 Spatial effect decomposition

Table 5 reports the effect decomposition of the core explanatory variable. The direct effect is about 0.26, marginally significant at the 10% level; the indirect effect is about -0.34, also significant at the 10% level; and the total effect is about -0.08, insignificant. The two effects point in opposite directions and offset each other, indicating that under the geographic-adjacency framework the digital economy is positively associated with local growth, whereas the digital economy development of neighboring areas is negatively associated with local growth. Aggregate-level regressions can hardly reveal this structure. The result contradicts the diffusion logic and is consistent with the competition or diversion logic—that is, digital resources may concentrate in pioneering regions, exposing neighboring areas to factor and market diversion. It should be emphasized that these effects are significant only at the 10% level, and both magnitude and significance are limited; this paper therefore describes the finding as a directional pattern rather than a

precise quantitative conclusion, and the exact interpretation of coefficients should remain cautious. Accordingly, Hypothesis 2 is supported in direction: the impact of the digital economy on smart logistics growth is not simple direct driving but a spatial pattern with opposite local and neighboring signs. The negative indirect effect is the focus of subsequent robustness checks—whether it persists under alternative settings directly determines the credibility of the judgment on the spatial competition structure and the final ordering of evidential strength. Figure 1 compares the effect decompositions under the four settings; error bars denote 90% confidence intervals.

Table 5
Spatial effect decomposition of the core explanatory variable

Effect type	Economic distance (short-run)	Rook adjacency (short-run)	Rook adjacency (three-year)
Direct effect	0.109 (0.118)	0.258* (0.134)	0.467 (0.314)
Indirect effect	-0.258 (0.247)	-0.341* (0.199)	-0.937* (0.517)
Total effect	-0.149 (0.272)	-0.082 (0.194)	-0.469 (0.581)
Observations	270	270	210
R ²	0.191	0.209	0.474
Fixed effects (province/year)	Yes/Yes	Yes/Yes	Yes/Yes
Note: Standard errors in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Short-run: growth specification; three-year: growth_3 year specification.			

4.4 Conditional features of the threshold effect

Table 6 reports the threshold test results. Under the two-year growth specification, neither the single threshold of financial deepening nor that of human capital passes the Bootstrap significance test, indicating that the moderating role of financial conditions has not emerged amid short-run fluctuations. Extending the window to three years, the single threshold of financial deepening is significant at the 5% level, with an F statistic of about 14.8, a threshold estimate of 2.062, and a confidence interval between 1.340 and 2.187. The regime estimates show that below the threshold the coefficient is near zero and insignificant, while beyond the threshold the coefficient jumps to about 0.48 and is significant at the 10% level. The augmented estimates show coefficients of 0.006 for urban and 0.001 for open, both insignificant, indicating that urbanization and openness do not drive the regime differences and that the stronger marginal role of X in the high-finance regime is not affected by controls. The double threshold of financial deepening fails the test, suggesting the non-linear structure is mainly a single critical point. Human capital still shows no significant threshold under the three-year specification, indicating that the threshold feature is not universal across supporting conditions. The sample mean is about 1.666, below the threshold, so most provinces' financial deepening has not reached the critical value. Note that the threshold model excludes spatial terms; its results should be read as conditional association features, and the sensitivity of the threshold findings to spatial settings is examined in the robustness checks. Figure 2 compares the regime coefficients across settings; error bars denote 90% confidence intervals.

Table 6
Threshold effect tests for financial deepening and human capital

Threshold variable	Specification	F statistic	Bootstrap p	Threshold / 95% CI	X regime coefficients
finance (short-run)	Single threshold	2.377	0.567	—	—
humancap (short-run)	Single threshold	1.409	0.750	—	—
finance (three-year)	Single threshold	14.843**	0.020	2.062 [1.340, 2.187]	Low: 0.023 (0.230); High: 0.481* (0.273)
finance (three-year)	Double threshold	2.426	0.751	—	—
humancap (three-year)	Single threshold	3.566	0.412	—	—
humancap (three-year)	Double threshold	5.658	0.468	—	—
Note: *, ** and *** denote significance at the 10%, 5% and 1% levels. Short-run: growth specification (N = 270); three-year: growth_3 year specification (N = 210). Under the three-year single threshold of finance, the control estimates are urban 0.006 (0.009) and open 0.001 (0.002), both insignificant.					

4.5 Identification boundary and endogeneity diagnostics

To delineate the evidential boundary, this paper conducts instrumental-variable diagnostics, with results in Table 7. The instruments are terrain ruggedness and the 1990 historical value of post and telecommunications business; the former reflects the natural cost of digital infrastructure construction, and the latter reflects the region's historical foundation of digitalization. Both correlate with the current digital economy level and satisfy relevance in theory. The estimates show that the joint F statistic of the two instruments is about 6.5—well below the conventional rule of thumb—suggesting weak instrument relevance. The second-stage coefficient of the digital economy is insignificant and its direction is inconsistent with the baseline; the Sargan–Hansen overidentification test cannot reject the null of exogeneity. The meaning of this diagnosis lies in clarifying the identification limits of this paper: weak instruments imply that the current data can hardly support strong causal identification, so the findings are positioned as the characterization of conditional associations rather than the final adjudication of causal effects. Any causal claim would exceed what the current data can support. It should be noted that the potential link of terrain ruggedness with logistics costs also makes its exclusion restriction disputable; causal identification is left to future research with better instruments or quasi-natural experiments. The statements of this paper remain consistent with this identification limit throughout.

Table 7
Instrumental-variable diagnostics

Variable / test	Estimate
First stage: terrain	0.021*** (0.006)
First stage: post1990	0.035 (0.029)
First-stage joint F	6.505 (p = 0.005)
Second stage: X	-0.032 (0.181)
Second stage: urban	0.000487 (0.000931)
Second stage: open	0.000427 (0.000271)
Sargan–Hansen test	$\chi^2 = 0.489$, p = 0.485
Observations	270
Note: Standard errors in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Instruments: terrain ruggedness and the 1990 historical value of post and telecommunications business volume; dependent variable: growth.	

4.6 Robustness checks

The robustness checks proceed in three directions, with results in Tables 8 and 9. The first direction changes the weight matrix and the growth window. Under the three-year specification, all effects remain insignificant under the economic distance matrix. Under the adjacency matrix, the spatially lagged explanatory variables are significantly negative at the 5% level and the indirect effect is significantly negative at the 10% level, consistent with the neighboring-negative pattern of the main results—the competitive spatial structure is not an artifact of a particular specification. The second direction excludes the pandemic years, re-estimating after dropping 2020–2022 from the sample. The local coefficient falls to 0.045 and becomes insignificant, indicating that the estimated positive local association is sensitive to pandemic disturbances: the local effect may be partly supported by the structural changes in logistics demand during the pandemic, and its explanatory power weakens markedly in normal years. In contrast, the coefficient on the spatial lag of neighboring provinces' digital economy is about -0.51 , still negative at the 10% level, and the indirect and total effects are also negative at the 10% level—the evidence for negative spatial spillover survives the exclusion of the pandemic. Taken together, the negative spatial spillover is the most consistent finding of this paper, while the robustness of the positive local association is clearly insufficient; this contrast provides the basis for the ordering of evidential strength in the conclusions.

Table 8
Robustness: alternative weight matrices and observation windows (three-year specification)

Variable / item	Economic distance matrix	Rook adjacency matrix
ρ / W·growth_3yr	-0.074 (0.352; p = 0.834)	0.269 (0.211; p = 0.204)
X	0.157 (0.229; p = 0.495)	0.517 (0.317; p = 0.103)
urban	-0.009 (0.013; p = 0.496)	0.006 (0.011; p = 0.581)
open	0.001 (0.002; p = 0.665)	0.002 (0.002; p = 0.511)
W·X	-0.407 (0.477; p = 0.393)	-0.861** (0.390; p = 0.027)
W·urban	-0.053** (0.026; p = 0.044)	-0.016 (0.030; p = 0.598)
W·open	0.002 (0.003; p = 0.616)	-0.008 (0.005; p = 0.136)
Direct effect	0.161 (0.236; p = 0.495)	0.467 (0.314; p = 0.136)
Indirect effect	-0.395 (0.475; p = 0.406)	-0.937* (0.517; p = 0.070)
Total effect	-0.234 (0.523; p = 0.655)	-0.469 (0.581; p = 0.419)
Wald test p-value	0.137	0.077
LR test p-value (SDM vs SAR)	0.204	0.008
LR test p-value (SDM vs SEM, approx.)	0.203	0.010
Observations	210	210
R ²	0.445	0.474
Note: Standard errors and p-values in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Dependent variable: three-year growth rate; urban and open enter at their three-year initial values.		

Table 9
Robustness: excluding the pandemic years

Variable / item	Estimate
ρ / W·growth_2yr	-0.105 (0.131; p = 0.422)
X	0.045 (0.185; p = 0.808)
urban	0.000 (0.008; p = 0.992)
open	0.002 (0.002; p = 0.368)
W·X	-0.508* (0.308; p = 0.100)
W·urban	0.002 (0.014; p = 0.880)
W·open	0.002 (0.004; p = 0.502)
Direct effect (X)	0.065 (0.192; p = 0.737)
Indirect effect (X)	-0.492* (0.288; p = 0.087)
Total effect (X)	-0.428* (0.253; p = 0.091)
Wald test	$\chi^2 = 3.890$, p = 0.274
LR test (SDM vs SAR)	$\chi^2 = 3.820$, p = 0.282
LR test (SDM vs SEM)	$\chi^2 = 3.760$, p = 0.288
Observations	150
Effective years	2017–2019, 2023–2024
Note: Standard errors and p-values in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Pandemic years 2020–2022 are excluded; weight matrix: Rook adjacency matrix; urban and open enter at their two-year initial values; dependent variable: two-year growth rate.	

The third direction tests the sensitivity of the threshold finding to spatial structure, with results in Table 10. After adding the spatially lagged controls of the Rook matrix to the main threshold model, the threshold estimate moves to 1.593, but the Bootstrap p-value is 0.790—no longer significant. Although the coefficients on both sides of the threshold are positive, the 0.40 of the low-finance regime actually exceeds the 0.31 of the high-finance regime, opposite to the regime pattern of the main results; the threshold evidence weakens markedly in the spatial framework. Notably, the coefficient on neighboring provinces' digital economy among the spatial controls is significantly negative at the 5% level, indicating that competitive spillover persists within the threshold framework, echoing the neighboring-suppression pattern of the main results. Figure 3 compares the estimated spillover coefficients of neighboring provinces' digital economy across the four settings; error bars denote 90% confidence intervals. The interpretation of the relationship between the threshold finding and spatial structure requires caution. One possibility is that the threshold effect in the main results is partly driven by spatial omission—neighboring competition being partly attributed to the role of financial conditions. Another possibility is that the limited sample weakens the discriminating power of the spatially augmented model. Under either interpretation, the threshold-type conditional association of financial deepening should be positioned as an exploratory finding, and its interweaving with the spatial competition structure awaits finer data. The conclusions will qualify the support for Hypothesis 3 accordingly.

Table 10
Spatially augmented threshold model

Item	Estimate
Model specification	Hansen fixed-effect threshold model with Rook spatial controls
Dependent variable	growth
Threshold variable	finance
Threshold estimate / 95% CI	1.593 [1.589, 1.593]
Bootstrap test	F = 2.020, p = 0.790 (300 replications)
X (low-finance regime)	0.400*** (0.151; p = 0.008)
X (high-finance regime)	0.308** (0.123; p = 0.013)
urban	0.012** (0.006; p = 0.041)
open	-0.001 (0.001; p = 0.379)
W·growth	0.183 (0.113; p = 0.106)
W·X	-0.277** (0.137; p = 0.044)
W·urban	-0.007 (0.006; p = 0.226)
W·open	-0.004* (0.002; p = 0.056)
Observations	270
Fixed effects	Province fixed effects
Note: Standard errors and p-values in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Spatial controls include W·growth, W·X, W·urban and W·open. The threshold effect fails the Bootstrap significance test and is reported as a spatially augmented approximation.	

4.7 Extension: a preliminary exploration of transmission mechanisms

As an extension, this paper preliminarily tests the transmission channels through which the digital economy affects smart logistics growth, with results in Table 11. The candidate mediator is the network density of logistics firms, on the logic that the digital economy may improve organizational efficiency by promoting the agglomeration and network expansion of logistics firms, thereby fostering smart logistics growth—a mechanism consistent with the networked nature of the logistics industry. Using stepwise regression and Bootstrap, the Sobel statistic is near zero and the confidence interval of the Bootstrap indirect effect contains zero, so the network-density channel is not supported [21]. This result rules out network density as a transmission channel and suggests that the paths of the digital economy may operate through technology diffusion, supply-chain coordination, or other mechanisms to be identified in future research. It should be noted that this extension is a preliminary exploration at the mechanism level; its sample is consistent with the main regressions, its conclusions do not alter the evidential-strength judgment on the three core findings, and it does not constitute reverse evidence against the main results. A complete identification of transmission mechanisms requires richer variables and finer data; this paper only makes limited judgments on the channels reachable by the current data and leaves the final determination of mechanisms to future research—an arrangement that also reflects respect for evidential boundaries.

Table 11
Mediation test results

Item	X	urban	open	M	N	R ²
Step 1 (X → M)	-0.162 (0.243)	0.073*** (0.015)	-0.008 (0.005)		270	0.996
Step 2 (X → growth)	0.075 (0.113)	0.007 (0.005)	-0.000815 (0.000778)		270	0.174
Step 3 (X + M → growth)	0.090 (0.114)	0.000285 (0.004)	-0.000108 (0.000933)	0.093*** (0.036)	270	0.192
Sobel test				Z = - 0.646, p = 0.518		
Bootstrap indirect effect				95% CI [-0.059, 0.022]		
Note: Standard errors in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. M is the network density of logistics enterprises; Bootstrap with 500 replications; all step regressions include province and year fixed effects.						

Placing the evidence together yields answers to the three questions. The local direct association between the digital economy and smart logistics growth fails significance tests under most settings—insignificant under the economic distance framework, only marginally positive under adjacency, and vanishing after excluding the pandemic—corresponding to Hypothesis 1. Under the geographic-adjacency channel, the negative spatial spillover persists across alternative weights, extended windows, pandemic exclusion, and spatial controls—the most consistent pattern in this paper—corresponding to the core of Hypothesis 2. Financial deepening constitutes a single threshold under the three-year non-spatial specification but becomes insignificant once spatial structure is incorporated, so the robustness of the threshold-type conditional association is limited, corresponding to exploratory support for Hypothesis 3. It should be emphasized that the conclusions are therefore limited to the characterization of conditional associations and pattern features, not strong causal judgments; the explanatory power of each finding should match its evidential strength. The three findings interlock and jointly point to one judgment: the logistics growth effect of the digital economy operates mainly through the spatial dimension, with the evidence for the local direct association and the financial threshold weakening in turn. Discussing its role apart from spatial structure and supporting conditions easily leads to one-sided understanding. The three links together form a closed-loop answer to the research question and provide a clear basis for the policy discussion in the conclusions.

5 Conclusions and policy implications

5.1 Main findings

Based on the panel data of 30 Chinese provinces over 2015–2024, this paper examines the conditional association between the digital economy and smart logistics growth from a growth-rate perspective. The main findings can be summarized in three points, with evidential strength declining in turn. The most robust finding is the negative spatial spillover: the digital economy development of neighboring provinces is negatively associated with local smart logistics growth, and this pattern persists under alternative weight matrices, extended windows, pandemic exclusion, and spatial controls, indicating that the impact of the digital economy on smart logistics growth operates mainly through the spatial dimension and that the interregional competition or diversion structure is consistent across settings. Second, robust evidence for the local direct association is lacking: all effects are insignificant under the economic distance framework, only marginally positive at the 10% level under geographic adjacency, and sensitive to the window and

pandemic disturbances. Third, the threshold-type conditional association of financial deepening passes the 5% test only under the three-year non-spatial specification and becomes insignificant once spatial structure is incorporated, so it should be positioned as an exploratory finding. The three findings jointly point to one judgment: there is no simple, automatic transformation between the digital economy and smart logistics growth; the effect is reorganized in space and constrained by conditions. In terms of evidential strength across the three hypotheses, Hypothesis 2 receives the most consistent support, Hypothesis 1 lacks robust evidence, and Hypothesis 3 is supported only under the non-spatial specification and becomes insignificant with spatial structure, so its strength is rated as exploratory rather than robust. Constrained by instrument quality and data structure, the evidence of this paper is positioned as a rigorous characterization of conditional associations.

5.2 Policy implications

The conclusions carry implications for policy design. First, policy evaluation should shift from input scale to transformation conditions. Since the local direct association is unstable, regions should not assume that digital inputs automatically bring logistics growth; instead, they should assess local transformation conditions and direct policy resources toward the links that can form real productivity. Assessment systems should likewise shift from construction progress to operational effectiveness. Second, spatial governance should give priority to the competitive structure—the best-supported part of this paper’s evidence. The coexistence of local-positive and neighboring-negative patterns suggests that digital economy hubs may divert resources from their periphery. At the national level, cross-regional digital logistics coordination should be promoted—data sharing, mutual recognition of standards, and network interconnection—to reduce substitutive competition across regions, so that the spillover of pioneering regions manifests more as diffusion than siphoning; this requires top-level design beyond administrative boundaries. Third, the policy implications of financial conditions should remain prudent: the threshold finding holds only under a specific specification and its interweaving with spatial structure awaits identification. Relevant policies should aim at improving the financing environment and lowering the digitalization threshold of logistics firms, rather than making detailed operational rules around a specific threshold value. The policy recommendations correspond to the research findings, and in view of the significance boundaries of the evidence, the statements are mainly directional.

5.3 Limitations and prospects

The limitations of this paper should be stated honestly. First, the provincial analysis may mask heterogeneity at the city and firm levels; the practical agents of smart logistics are firms, and the micro-foundations of the interprovincial pattern await refinement. Second, mechanism identification is not closed: the network-density channel is not supported, and candidate channels such as platform-based operation, data-element use, and supply-chain coordination deserve testing on finer data. Third, causal identification is constrained by instrument quality; the exclusion restriction of terrain ruggedness is disputable, and future work may construct more credible identification strategies via policy pilots and other quasi-natural experiments. Fourth, the threshold finding is sensitive to the spatial setting and becomes insignificant once spatial structure is incorporated; this paper therefore positions it as exploratory. The interweaving of the threshold effect and the spatial competition structure awaits finer data, and this uncertainty should be conveyed honestly. Fifth, the sample period includes the COVID-19 phase; the local effect weakens markedly after excluding the pandemic, the pandemic’s influence is not separately modeled, and the relevant results should be interpreted cautiously against this background. In addition, the explained variable is the growth rate of a composite index without a natural economic unit, and the overlapping three-year window raises serial-correlation concerns. Future research may proceed at the city or firm level and improve identification with exogenous shocks; sustained empirical tracking remains necessary, and the findings of this paper provide a testable benchmark for such work.

Declarations

Author Contribution

C.S. conceptualized the study, performed the empirical analysis, prepared Figures 1–3 and Tables 1–11, and wrote the main manuscript text; L.X. and T.W. curated the data and participated in the robustness checks; P.Z. supervised the research and revised the manuscript. All authors reviewed and approved the manuscript.

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Figures

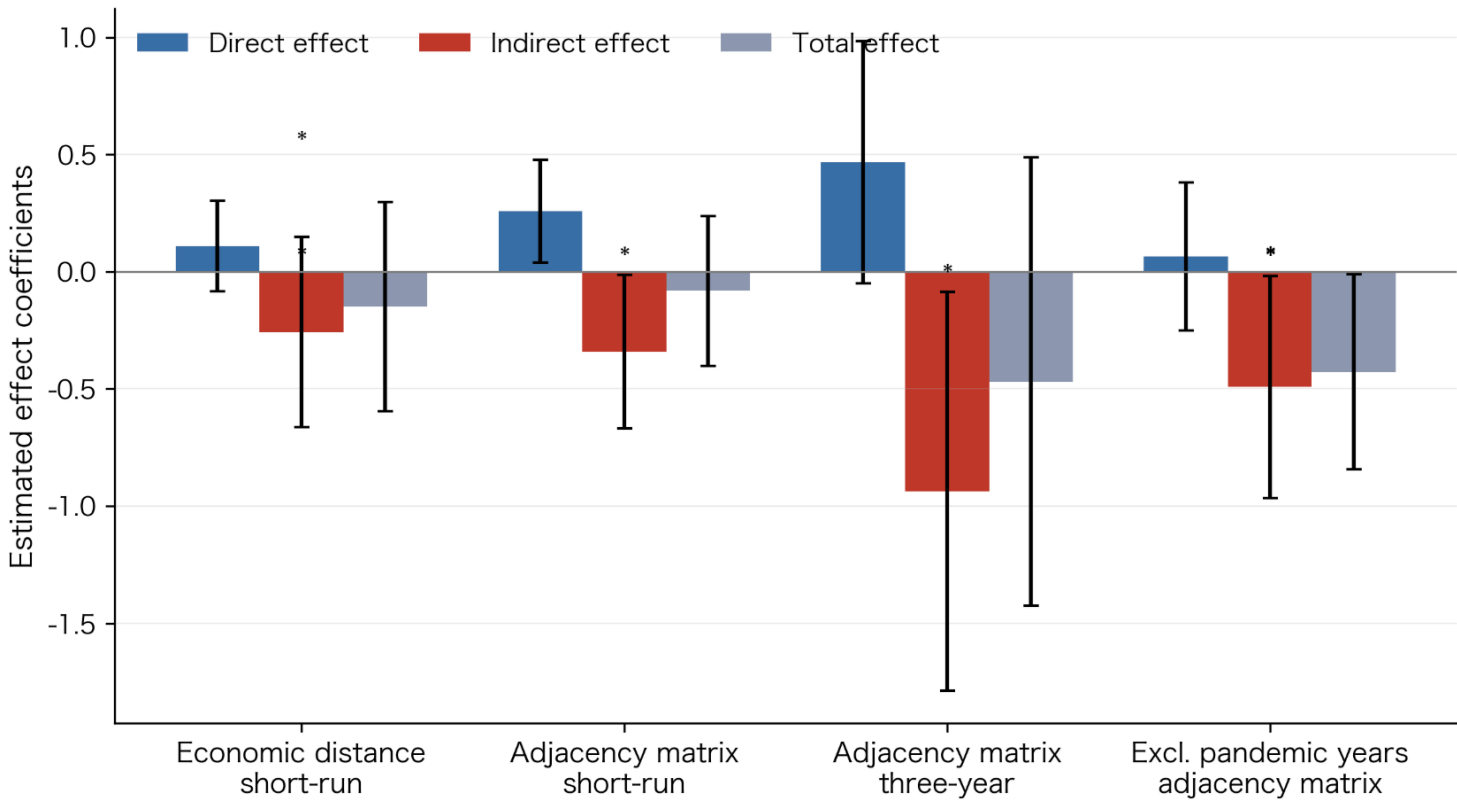


Figure 1

Spatial effect decomposition of the digital economy on smart logistics growth: comparison across four settings

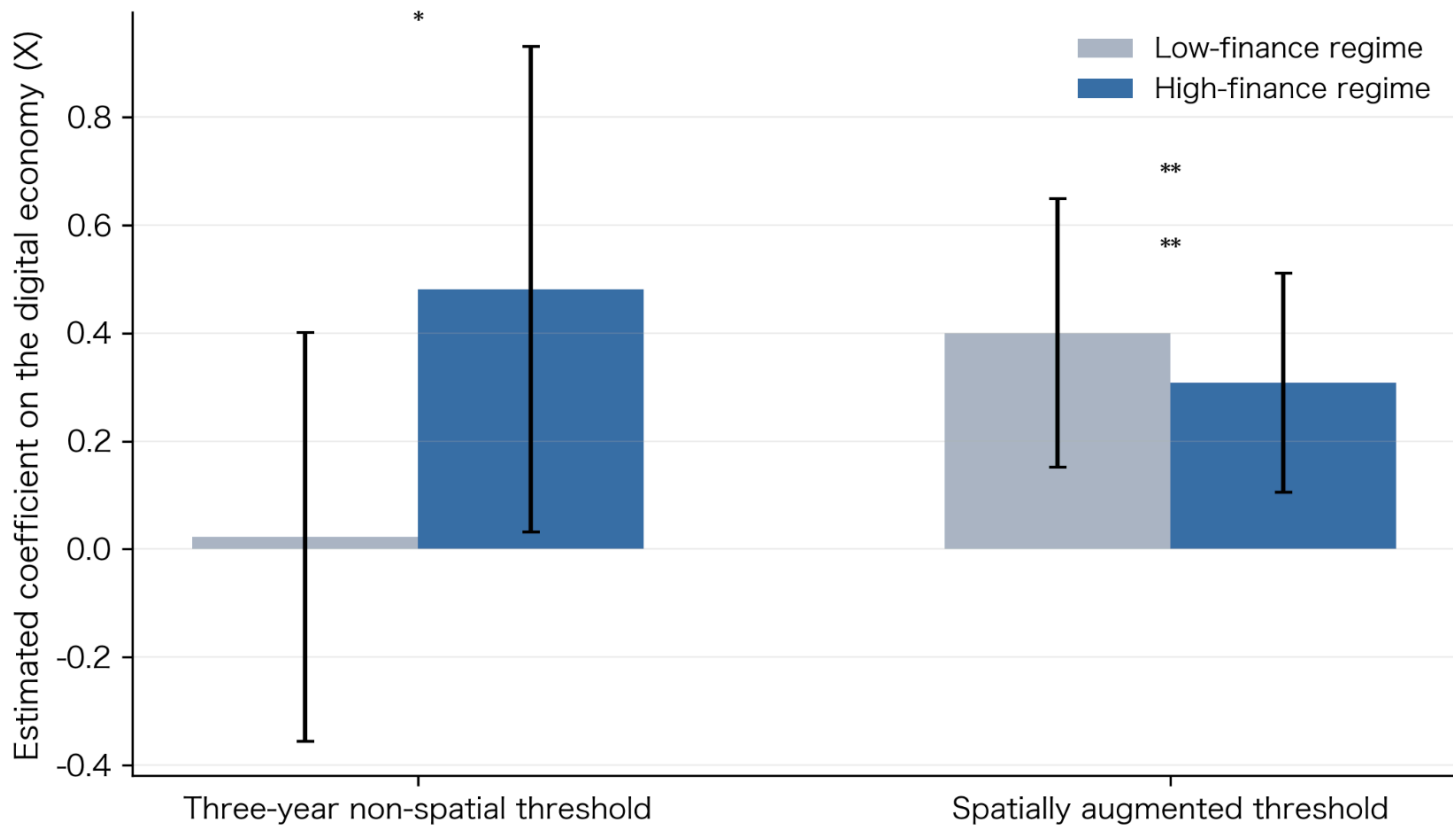


Figure 2

Regime coefficients of the financial deepening threshold

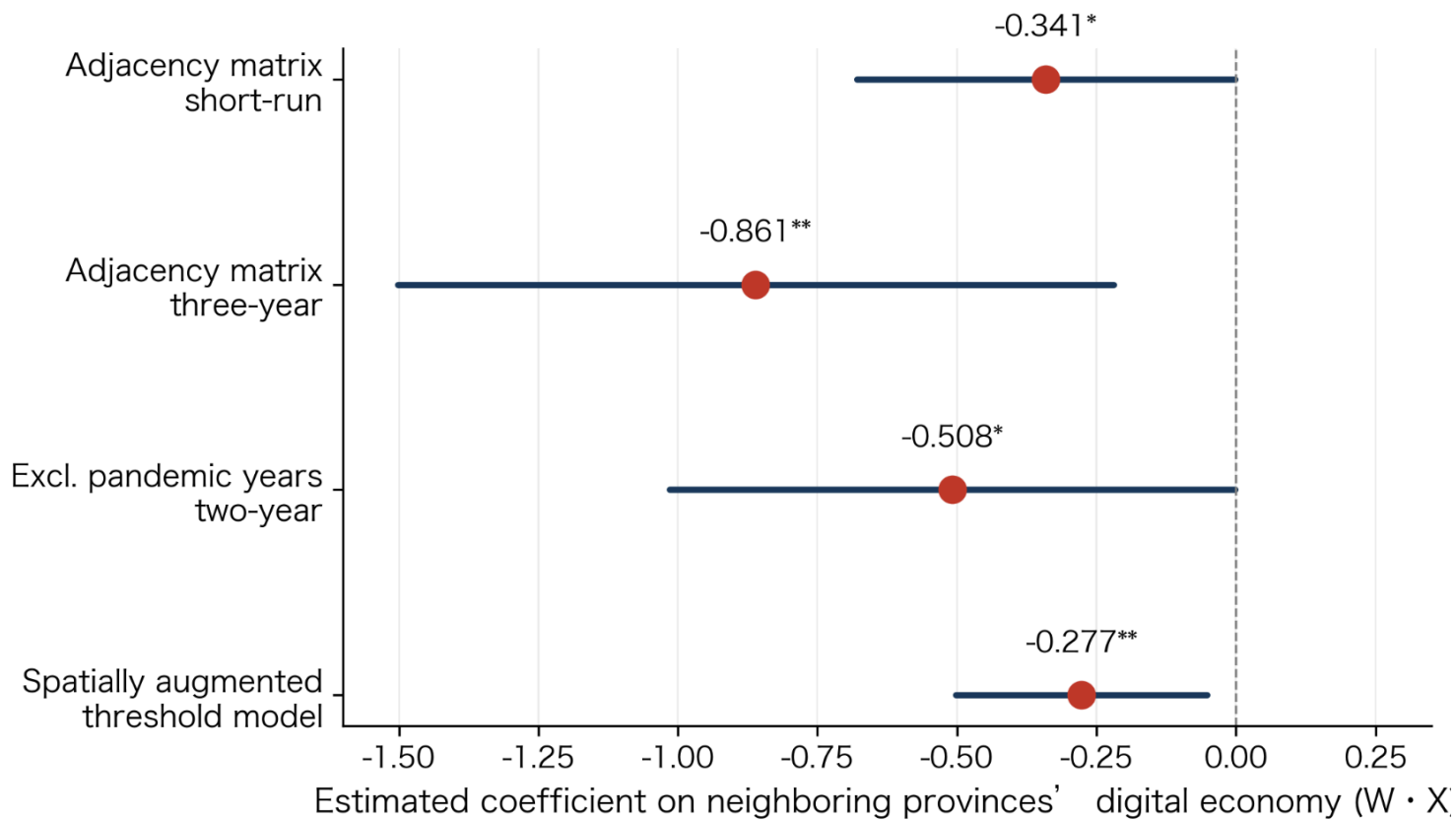


Figure 3

Spatial spillover coefficients of neighboring provinces' digital economy: robustness across four settings

Supplementary Files

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- [AppendixA.docx](#)