



OPEN Spatial spillovers in producer services–manufacturing coordination: evidence from Chinese provinces

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Against the backdrop of China’s “dual carbon” agenda and the push for high-quality development, coordinated development between producer services and manufacturing is increasingly viewed as a pathway for industrial upgrading. However, evidence on the spatiotemporal evolution and spatial spillovers of this integration across China’s provinces remains limited. Using panel data for 31 provincial-level regions in China from 2013 to 2022, we construct entropy-weighted composite indices and quantify integration with a coupling coordination degree (CCD) model. Spatial dependence is assessed via global Moran’s I and local indicators of spatial association (LISA), and a spatial Durbin model (SDM) with effect decomposition is estimated to examine determinants and spillovers. CCD increases steadily over time but remains uneven, exhibiting a persistent east–central–west gradient with significant positive spatial autocorrelation and stable local clusters. General public service expenditure raises CCD mainly through within-province effects, and its spillover effects are comparatively weaker, whereas residents’ income and informatization strengthen CCD largely via positive spillovers to neighboring provinces. Industrial structure and labor force level show negative direct effects on CCD. Robustness checks confirm these findings. These results underscore the importance of strengthening local public services and cross-regional coordination to improve integration performance and better leverage spillovers. The “dual carbon” agenda is treated as policy context rather than a directly measured environmental outcome.

Keywords Producer services, Manufacturing, Coupling coordination, Spatial spillovers, Spatial Durbin model

As globalization and economic integration deepen, optimizing and upgrading industrial structures has become an important concern for economic development worldwide^{1–3}. Producer services are widely recognized as expertise-intensive, talent-intensive, and information-intensive activities that can improve economic quality and enhance global competitiveness^{4,5}. In China, the “dual carbon” agenda and the broader push for high-quality development have increased the policy relevance of upgrading producer services and manufacturing. Meanwhile, China has risen rapidly as the “world’s manufacturing factory” by leveraging cost advantages in labor, capital, and land resources. China’s manufacturing sector has expanded rapidly and has long been predominantly labor-intensive^{6,7}. Under the new development pattern, manufacturing is increasingly shifting from factor-driven expansion toward innovation-driven upgrading, and policy documents emphasize sustainable and intelligent transformation^{8,9}. Recent statistics show that China’s industrial gross output value reached 39.91 trillion yuan in 2023, accounting for 31.65% of GDP. Manufacturing accounted for 25.87% of GDP, and China has maintained the world’s largest industrial scale for 14 consecutive years¹⁰. These figures underscore the scale of manufacturing and the urgency of upgrading its development model. They also reinforce the practical relevance of examining how producer services can support manufacturing transformation through deeper coordination.

In recent years, industrial policies enacted by the Chinese government have outlined the strategic objective of facilitating deep convergence between producer services and manufacturing alongside the modernization of the industrial system^{11–13}. This strategic deployment indicates that the relationship between producer services and manufacturing, hereafter referred to as the two sectors, is transforming from one-way dependence to mutual

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support and co-evolution^{14–18}. This industrial synergy can optimize resource allocation and enhance total factor productivity. It can also reduce cross-sector barriers and promote the diffusion of innovation factors, driving the industrial chain and value chain to move toward high-end development^{19–21}. From an industrial interaction standpoint, producer services can strengthen coordination efficiency and knowledge diffusion in manufacturing by improving financing conditions, R&D support, logistics capability, and informatization. Conversely, manufacturing upgrading reshapes demand for specialized services and can stimulate service specialization and scale^{22,23}. While these interactions are plausibly relevant to sustainability-oriented upgrading, the empirical focus of this study is the integration performance of the two sectors as measured by CCD, rather than direct environmental outcomes^{24–27}. The “dual carbon” agenda is treated as policy context for interpreting upgrading-related channels, while CCD remains the outcome variable.

A coherent explanation of coordinated development between the two sectors requires a framework that links the definition of coordination, the selection of drivers, and the logic of spatial interaction. This study integrates three complementary perspectives and translates them into analytical implications that guide measurement, variable selection, and model design. Together, these perspectives motivate the outcome definition, the driver set, and the need to identify spatial dependence and spillovers.

First, complex adaptive systems thinking treats producer services and manufacturing as interdependent subsystems. Their feedback and adaptation generate a system-level coordination outcome. This perspective motivates the use of CCD as the dependent variable because CCD captures the system-level state of coordination rather than single-sector performance.

Second, new structural economics highlights that sectoral coordination depends on local endowments, structural conditions, and the enabling role of public goods provision in facilitating structural transformation. This logic motivates our focus on local enabling conditions and transformation factors, including general public service expenditure, income conditions, structural upgrading, informatization, and labor force conditions. Existing evidence on integration mechanisms emphasizes that producer services agglomeration and the adoption and embedding of digital technologies can reshape manufacturing upgrading and strengthen producer services–manufacturing linkages. This supports treating structural upgrading and informatization as key channels^{28–30}.

Third, evolutionary economic geography emphasizes path dependence, proximity-based externalities, and diffusion through interregional networks. It implies that coordination outcomes may cluster spatially and that key drivers may produce spillovers across provincial borders through technology diffusion, factor mobility, market linkages, and policy learning. Empirical studies on coordinated development and green upgrading have documented spatial effects and spatiotemporal dependence patterns. These findings are consistent with the expectation that CCD and its determinants may exhibit spatial dependence in China’s provincial context^{21–34}.

These theoretical implications require an empirical strategy that identifies both within-province effects and spillover effects. Spatial econometric approaches have been widely applied in coupling coordination research to examine spatial dependence and to separate direct effects from indirect effects under alternative interregional linkages^{35–38}. Accordingly, this study characterizes spatial dependence using Moran’s I and LISA. It then estimates an SDM and conducts effect decomposition to distinguish within-province effects from spillover effects of key driving factors.

Existing literature on producer services and manufacturing integration has made important progress, but gaps remain regarding how CCD evolves and what drives it. Much research focuses on agglomeration, industrial interaction, and network embedding, including policy-driven agglomeration and cross-regional evolution mechanisms^{39–41}. Certain studies evaluate the degree of coordinated development of the two sectors from industrial and regional viewpoints⁴². Other work analyzes driving factors using non-spatial regression frameworks that implicitly treat provinces as independent units⁴³. Nonetheless, three limitations remain. First, the dynamic evolution of CCD has not been examined in sufficient depth. Second, systematic investigation into the spatial spillover effects of key drivers remains scarce, despite the likelihood that diffusion and mobility operate across provincial borders. Third, although many studies discuss integration within sustainability-oriented policy narratives, the measurement boundary between integration performance and environmental outcomes is often not stated explicitly, which can create a positioning tension. These three limitations directly motivate our contributions on measurement, spatial spillover identification, and positioning.

To address these gaps, this study is guided by two research questions. The first research question concerns whether CCD exhibits significant spatial dependence and how it evolves over time and across space in China from 2013 to 2022. The second research question concerns which drivers shape CCD and whether they operate mainly through within-province effects or spatial spillovers. To answer the first question, this study constructs composite development indices for the two sectors and quantifies CCD to document its spatiotemporal evolution. To answer the second question, it estimates an SDM and conducts effect decomposition to identify both direct impacts and spatial spillovers of key driving forces. Spatial dependence is further characterized using Moran’s I and LISA. Future research can strengthen low-carbon evidence by incorporating direct indicators such as carbon intensity or environmental efficiency as additional outcomes or as components of the evaluation system.

Based on Chinese provincial panel data from 2013 to 2022, this study makes three contributions. First, it provides a reproducible province-year measure of CCD and documents its spatiotemporal evolution, thereby advancing evidence on dynamic evolution. Second, by embedding CCD in an SDM and conducting effect decomposition, it identifies not only whether key drivers matter, but also whether they operate primarily through within-province effects or through spatial spillover channels. Third, it develops policy-relevant implications under the high-quality development agenda and clarifies the measurement boundary between integration performance and environmental outcomes. This aligns the paper’s positioning with what is empirically measured while treating the “dual carbon” agenda as policy context.

Research methods and selection of indicator variables

Entropy-weight method

In a multi-indicator comprehensive evaluation, an objective weighting scheme helps reduce subjectivity in index construction. This study applies the entropy-weight method separately to each subsystem to derive indicator weights and construct a composite development index for each province-year observation.

Data standardization

Due to differences in units and magnitudes across indicators, the original data are standardized using the min-max method. Let X_{ptj} denote the original value of indicator j for province p in year t , and let N denote the number of provinces. The min and max operators are taken across provinces within the same year t .

$$\text{Positive effect indicators. } Z_{ptj} = \frac{x_{ptj} - \min_p(x_{ptj})}{\max_p(x_{ptj}) - \min_p(x_{ptj})} \quad (1)$$

$$\text{Negative effect indicators. } Z_{ptj} = \frac{\max_p(x_{ptj}) - x_{ptj}}{\max_p(x_{ptj}) - \min_p(x_{ptj})} \quad (2)$$

Indicator proportions

For each year t and indicator j , the proportion of province p is defined as

$$\mathcal{Y}_{ptj} = \frac{z_{ptj}}{\sum_{p=1}^N z_{ptj}}. \quad (3)$$

When $\sum_{p=1}^N z_{ptj} = 0$, we set $\mathcal{Y}_{ptj} = \frac{1}{N}$ for all p to ensure that the entropy measure is well defined.

Information entropy of indicators

The information entropy of indicator j in year t is computed as

$$e_{tj} = -k \sum_{p=1}^N (\mathcal{Y}_{ptj} \times \ln \mathcal{Y}_{ptj}), \quad (4)$$

where $k = \frac{1}{\ln(N)}$ ensures that $0 \leq e_{tj} \leq 1$. When $\mathcal{Y}_{ptj} = 0$, we set $\mathcal{Y}_{ptj} \times \ln \mathcal{Y}_{ptj} = 0$.

Entropy redundancy

The information utility (redundancy) of indicator j in year t is defined as

$$d_{tj} = 1 - e_{tj}. \quad (5)$$

A larger d_{tj} indicates greater information content and thus a higher contribution of that indicator to differentiating provinces in that year.

Indicator weights

The entropy-weight of indicator j in year t is given by

$$w_{tj} = d_{tj} / \sum_{j=1}^n d_{tj}, \quad (6)$$

where n denotes the number of indicators within the subsystem. This weighting scheme ensures $\sum_{j=1}^n w_{tj} = 1$.

Comprehensive evaluation

The comprehensive development index of the subsystem for province p in year t is calculated as a weighted sum of standardized indicators.

$$S_{pt} = \sum_{j=1}^n w_{tj} z_{ptj}. \quad (7)$$

In Eqs. (1)–(2), x_{ptj} and z_{ptj} represent the original and standardized values of indicator j , respectively, and the min and max operators are taken across provinces in the same year. Equations (3)–(6) define the entropy-based weights, and Eq. (7) yields the composite index S_{pt} for each province year observation. The above procedure is implemented separately for the producer services subsystem and the manufacturing subsystem to obtain their respective composite development indices, denoted as S_{pt}^{PS} and S_{pt}^M , which are subsequently used in the coupling coordination analysis.

Coupling coordination degree model

This study treats the development of producer services and manufacturing as two interacting subsystems and evaluates their coordinated development from four dimensions: industry scale, economic efficiency, development potential, and social benefits^{44–46}.

Let p denote province and t denote year. Let S_{pt}^{PS} and S_{pt}^M denote the composite development indices of producer services and manufacturing, respectively, which are computed using the entropy-weight method in

Sect. 2.1 (Eq. (7)). The coupling degree C_{pt} , the comprehensive coordination index T_{pt} , and CCD D_{pt} are defined as follows:

$$\begin{aligned}
 C_{pt} &= 2 \times \frac{S_{pt}^{PS} \times S_{pt}^M}{(S_{pt}^{PS} + S_{pt}^M)^2}, \\
 T_{pt} &= \alpha S_{pt}^{PS} + \beta S_{pt}^M, \\
 D_{pt} &= \sqrt{C_{pt} \cdot T_{pt}}.
 \end{aligned}
 \tag{8}$$

In Eq. (8), C_{pt} measures the strength of interaction between the two subsystems, T_{pt} reflects their overall development level, and D_{pt} represents the CCD. A larger D_{pt} indicates a higher level of coordinated development between producer services and manufacturing. Parameters α and β are weighting factors that reflect the relative importance of the two subsystems. Consistent with the common practice in the literature, this study assumes equal importance and sets $\alpha = \beta = 0.5$.

Following standardized CCD classification protocols, Table 1 presents the corresponding ten-level categorization criteria for interpreting the value of D_{pt} .

Spatial Moran’s index

To examine whether the CCD exhibits spatial dependence across Chinese provinces, this study employs the global Moran’s I statistic. Let D_{pt} denote the CCD value of province p in year t , where $p = 1, 2, \dots, N$ and $N = 31$. The global Moran’s I for year t is calculated as

$$I_t = \frac{\sum_{p=1}^N \sum_{q=1}^N w_{pq} (D_{pt} - \bar{D}) (D_{qt} - \bar{D}_t)}{s_t^2 \sum_{p=1}^N \sum_{q=1}^N w_{pq}}.
 \tag{9}$$

where $\bar{D}_t = \frac{1}{N} \sum_{p=1}^N D_{pt}$, $s_t^2 = \frac{1}{N} \sum_{p=1}^N (D_{pt} - \bar{D}_t)^2$, and w_{pq} are the (p, q) element of the spatial weight matrix W . In this study, W is constructed as a binary queen-contiguity matrix: $w_{pq} = 1$ if provinces p and q share a common border or vertex, and $w_{pq} = 0$ otherwise. The diagonal elements satisfy $w_{pp} = 0$.

A positive Moran’s I indicates spatial clustering of similar CCD levels across neighboring provinces, whereas a negative Moran’s I indicates spatial dispersion. Statistical significance is evaluated using the normal approximation. Specifically, the standardized Z statistic is computed as

$$Z(I_t) = \frac{I_t - E(I_t)}{\sqrt{Var(I_t)}}.
 \tag{10}$$

where $E(I_t)$ and $Var(I_t)$ denote the theoretical expectation and variance of Moran’s I under the null hypothesis of spatial randomness. Under a two-sided test at the 5% significance level, $|Z(I_t)| > 1.96$ indicates statistically significant spatial autocorrelation.

Spatial econometric models

Spatial econometric models are widely used to analyze panel data with spatial dependence. This study focuses on three standard specifications, namely the SAR model, the spatial error (SEM) model, and the SDM model. The SAR model captures spatial dependence through the spatial lag of the dependent variable, whereas the SEM model captures spatial dependence through the error term. The SDM nests the SAR and SEM as special cases and allows spatial dependence in both the dependent variable and the explanatory variables, which makes it suitable for identifying spatial spillovers.

To examine how key drivers affect CCD D_{pt} , this study follows a stepwise specification strategy. First, SAR and SEM are estimated as benchmark models. Second, diagnostic tests including the LM test and robust LM test are used to assess residual spatial dependence and to guide the choice of specification. Third, the SDM is selected as the main model, and the Wald test and LR test are used to examine whether the SDM can be simplified to the SAR or SEM. The SDM with province fixed effects is specified as follows.

$$D_{pt} = \alpha + \rho \sum_{q=1}^N w_{pq} D_{qt} + \beta X_{pt} + \sum_{q=1}^N w_{pq} X_{qt} \theta + \mu_p + \epsilon_{pt}
 \tag{11}$$

| Coupling coordination level | Extreme Dissonance | Severe Dissonance | Intermediate Dissonance | Primary Dissonance | Threatened Dissonance |
|-------------------------------------|--------------------|----------------------|---------------------------|--------------------|-----------------------|
| Coupled coordination D-value | 0.00 < D ≤ 0.10 | 0.10 < D ≤ 0.20 | 0.20 < D ≤ 0.30 | 0.30 < D ≤ 0.40 | 0.40 < D ≤ 0.50 |
| Coupling coordination level | Barely coordinated | Primary coordination | Intermediate coordination | Good coordination | Quality coordination |
| Coupled coordination D-value | 0.50 < D ≤ 0.60 | 0.60 < D ≤ 0.70 | 0.70 < D ≤ 0.80 | 0.80 < D ≤ 0.90 | 0.90 < D ≤ 1.00 |

Table 1. Classification criteria for CCD (D_{pt}).

In formula (11), D_{pt} denotes the coupling coordination degree of province p in year t . α is the constant term. $W = (w_{pq})$ is the spatial weight matrix constructed using the queen contiguity criterion described in Sect. 2.3, with $w_{pp} = 0$, and W is row-standardized so that $\sum_{q=1}^N w_{pq} = 1$. ρ is the spatial autoregressive coefficient. X_{pt} is a vector of explanatory variables. β and θ are coefficient vectors associated with local covariates and their spatial lags, respectively. μ_p represents the province fixed effects. ϵ_{pt} is the error term.

Measurement and analysis of the coordination degree between the producer services and the manufacturing

Data sources and processing

This study draws on four official data sources, namely the *China Economic Census Yearbook*, the *China Statistical Yearbook*, the *China Industrial Statistical Yearbook*, and the *China Tertiary Industry Statistical Yearbook*. These sources provide annual, province-level data on producer services and manufacturing for 31 provinces in China, excluding Hong Kong, Macao, and Taiwan, over the period 2013 to 2022. The resulting indicators cover economic output, employment-related measures, and sectoral structure variables, which are used to construct the composite development indices and CCD.

Missing values were handled using linear interpolation within each province over time to maintain a balanced panel. This approach was applied only when data gaps were limited, with missing observations accounting for less than 10% for each indicator. Sensitivity to imputation was assessed through robustness checks that compared the main results with alternative treatments of missing data, including deleting interpolated observations and using mean substitution. The results indicate that interpolation does not materially affect the findings.

Evaluation index system of coupling coordination degree between producer services and manufacturing

An evaluation index system was constructed to measure the development level of producer services and manufacturing. Consistent with composite index approaches that evaluate industrial performance through multiple dimensions rather than a single output measure, sectoral development is conceptualized as a multidimensional construct reflecting capacity, efficiency, growth potential, and social outcomes⁴⁷. Accordingly, the indicator system is organized into four first-level dimensions, namely industry scale, economic efficiency, development potential, and social benefits. The entropy weight method is applied to assign objective weights and compute composite development indices for each sector, which are then used to calculate CCD.

Industry scale captures the basic capacity foundation of each sector and is measured by the number of legal entities, sector gross domestic product, and total fixed asset investment, which jointly reflect organizational base, output capacity, and capital accumulation that can support upgrading and deeper service embedding. Economic efficiency captures development quality and is measured by labor productivity, profit margin, and cost-expense related indicators, which reflect productivity performance, profitability, and cost control. Productivity and its links to wages and employment are widely used for assessing efficiency-related development quality⁴⁸, and manufacturing and services integration has been shown to influence resource allocation and manufacturing labor productivity, which supports the use of efficiency indicators in this integration context⁴⁹. Development potential reflects the capacity for sustained expansion and upgrading and is proxied by the sector value-added share within the tertiary or secondary industry and the growth rates of value added, total profit, and income, capturing both structural position and growth momentum. Social benefits are represented by average wage and number of employees, reflecting inclusive outcomes and the labor market relevance of sectoral development, which is consistent with broader performance assessment perspectives that incorporate social aspects alongside competitiveness and efficiency.

The entropy-weight method determines indicator weights based on information content and dispersion, which helps reduce subjectivity in weighting and aggregation. This is consistent with recent research emphasizing objective and transparent procedures for constructing composite performance indicators⁵⁰. The indicator system and the corresponding entropy-based weights are reported in Table 2. The stability of the weighting scheme is examined through robustness tests, confirming that the main conclusions are not driven by a particular weighting configuration. The dual carbon agenda is used as a policy context to motivate the relevance of sustainability-oriented upgrading, while the empirical measurement in this study focuses on integration performance as captured by CCD rather than direct environmental outcomes.

Measurement of the coupling coordination degree between the producer services and manufacturing

Following Eqs. (1) and (2), all indicators were standardized using min–max scaling, with positive-effect and negative-effect indicators treated accordingly. The entropy weight method was then applied to derive indicator weights (Eqs. (3)–(6)) and compute the composite development indices for each subsystem (Eq. (7)). Specifically, the composite development indices were denoted as S_{pt}^{PS} and S_{pt}^M , calculated separately for each subsystem. Based on S_{pt}^{PS} and S_{pt}^M , we computed the coupling degree C_{pt} , the comprehensive coordination index T_{pt} , and CCD D_{pt} using Eq. (8), with subsystem weights set to $\alpha = \beta = 0.5$. The resulting province-year CCD values for 31 provinces from 2013 to 2022 are reported in Table 3, with results summarized by the eastern, central, and western economic zones. CCD levels were further interpreted using the ten-level classification criteria reported in Table 1. Spatial dependence and local clustering patterns of CCD were examined using Moran's I and LISA based on a first-order queen-contiguity spatial weight matrix W . The same W specification is used consistently in the spatial dependence tests and the SDM estimation.

| Subsystem | First-level Indicator | Second-level Indicator | Unit | Weight | Variable |
|---------------------|-----------------------|---|----------------------------|--------|----------|
| Producer Services | Industry Scale | Legal Entities | Units | 0.158 | X1 |
| | | Gross Domestic Product | Billion Yuan | 0.138 | X2 |
| | | Total Fixed Asset Investment | Billion Yuan | 0.095 | X3 |
| | Economic Efficiency | Labor Productivity | Billion Yuan/10,000 People | 0.077 | X4 |
| | | Profit margin of producer services revenue | % | 0.111 | X5 |
| | | Cost Profit Expense Ratio of the Producer services | % | 0.121 | X6 |
| | Development Potential | The Proportion of Added Value of Producer services in the Added Value of the Tertiary Industry | % | 0.029 | X7 |
| | | Growth Rate of Producer services | % | 0.018 | X8 |
| | | Growth Rate of Total Profit of Producer services | % | 0.082 | X9 |
| | | The growth rate of income from producer services | % | 0.016 | X10 |
| | Social Benefits | Average Wage of Employees in the Producer services | Yuan | 0.055 | X11 |
| | | Number of Employees | Persons | 0.102 | X12 |
| Manufacturing | Industry Scale | Legal Entities | Units | 0.250 | Y1 |
| | | Gross Domestic Product | Billion Yuan | 0.138 | Y2 |
| | | Total Fixed Asset Investment | Billion Yuan | 0.179 | Y3 |
| | Economic Efficiency | Labor Productivity | Billion Yuan/10,000 People | 0.080 | Y4 |
| | | Profit Margin of the Manufacturing | % | 0.003 | Y5 |
| | | Cost-Expense Ratio of Manufacturing | % | 0.004 | Y6 |
| | Development Potential | The proportion of the Added Value of the Manufacturing in the Added Value of the Secondary Industry | % | 0.013 | Y7 |
| | | Growth Rate of Manufacturing | % | 0.034 | Y8 |
| | | Growth Rate of Total Profit of Manufacturing | % | 0.013 | Y9 |
| | | The growth rate of income from the Manufacturing | % | 0.024 | Y10 |
| | Social Benefits | Average Wage of Employees in the Manufacturing | Yuan | 0.055 | Y11 |
| Number of Employees | | Persons | 0.208 | Y12 | |

Table 2. Index System for Coupling Coordination Degree between Producer Services and Manufacturing.

Analysis of the coupling coordination degree between producer services and manufacturing

Using the province-year CCD values (hereafter denoted as D) for 31 provinces from 2013 to 2022 (Table 3), the coupling coordination between producer services and manufacturing shows a gradual upward trend nationwide. However, most provinces remained in the dissonance categories defined in Table 1 ($D \leq 0.50$), indicating that the improvement in CCD has not translated into broadly coordinated development in most provinces. Notably, the number of provinces with $D > 0.50$ increased from 5 in 2013 to 9 in 2022. These provinces were mainly located in the eastern region (6 of 11) and the central region (3 of 8). No western province reached $D > 0.50$ in 2022, indicating a persistent east–central–west gradient in coordination outcomes.

Figure 1 further shows that the eastern region had the highest CCD levels. In 2022, D ranged from 0.420 to 0.765, spanning Threatened Dissonance ($0.40 < D \leq 0.50$) to Intermediate coordination ($0.70 < D \leq 0.80$) according to Table 1. Jiangsu, Zhejiang, Shandong, and Guangdong maintained $D > 0.50$ for most years, suggesting relatively stable coordination between the two sectors. Guangdong ranked first in 2022 ($D = 0.765$; Table 3). In contrast, Hainan and Tianjin remained at comparatively low levels, with ten-year mean values of 0.291 (Hainan) and 0.375 (Tianjin), indicating substantial within-region heterogeneity in coordination outcomes.

As shown in Fig. 2, the central region exhibits relatively low CCD levels, ranging from 0.304 to 0.561, and overall falls mainly within the dissonance categories, particularly Primary Dissonance ($0.30 < D \leq 0.40$) and Threatened Dissonance ($0.40 < D \leq 0.50$). At the same time, some provinces reached the coordination category of Barely coordinated ($0.50 < D \leq 0.60$). Henan performs best, with CCD values consistently above 0.50 over 2013–2022 (0.514–0.561) and a ten-year mean of 0.535. By contrast, Heilongjiang records the lowest long-term performance, with a ten-year mean of 0.347, which corresponds mainly to Primary Dissonance according to Table 1. Overall, CCD in the central region improves gradually, yet most provinces do not sustain $D > 0.50$ over time, suggesting that coordinated development between the two sectors remains uneven.

As presented in Fig. 3, the western region records the lowest CCD, ranging from 0.227 to 0.496, and does not reach the coordination categories defined in Table 1 ($D > 0.50$) throughout the observation period. Sichuan leads the western region, with a ten-year mean of 0.455 and rising to 0.496 in 2022, which remains within Threatened Dissonance ($0.40 < D \leq 0.50$) according to Table 1. Ningxia remains among the weakest performers, with a ten-year mean of 0.272, mainly within Intermediate Dissonance ($0.20 < D \leq 0.30$). These patterns indicate that, despite an upward trajectory, the western region has not yet formed a stable coordination pattern comparable to the eastern region and the leading central provinces.

In sum, CCD exhibits pronounced regional heterogeneity, with a clear east–central–west gradient and substantial within-region differences. Differences in structural upgrading and factor allocation may be associated

| | Province | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---------|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| East | Beijing | 0.388 | 0.344 | 0.384 | 0.391 | 0.393 | 0.444 | 0.399 | 0.411 | 0.439 | 0.429 |
| | Tianjin | 0.381 | 0.347 | 0.383 | 0.385 | 0.373 | 0.412 | 0.351 | 0.361 | 0.377 | 0.375 |
| | Hebei | 0.463 | 0.438 | 0.462 | 0.478 | 0.498 | 0.530 | 0.495 | 0.509 | 0.525 | 0.535 |
| | Liaoning | 0.469 | 0.416 | 0.429 | 0.370 | 0.391 | 0.410 | 0.376 | 0.373 | 0.399 | 0.392 |
| | Shanghai | 0.426 | 0.386 | 0.424 | 0.433 | 0.441 | 0.470 | 0.442 | 0.451 | 0.471 | 0.468 |
| | Jiangsu | 0.653 | 0.625 | 0.668 | 0.673 | 0.703 | 0.759 | 0.706 | 0.720 | 0.750 | 0.756 |
| | Zhejiang | 0.558 | 0.523 | 0.551 | 0.568 | 0.584 | 0.626 | 0.598 | 0.619 | 0.645 | 0.653 |
| | Fujian | 0.448 | 0.417 | 0.457 | 0.453 | 0.479 | 0.523 | 0.488 | 0.501 | 0.527 | 0.532 |
| | Shandong | 0.610 | 0.577 | 0.608 | 0.623 | 0.632 | 0.668 | 0.621 | 0.642 | 0.673 | 0.677 |
| | Guangdong | 0.646 | 0.622 | 0.644 | 0.657 | 0.687 | 0.731 | 0.733 | 0.742 | 0.760 | 0.765 |
| | Hainan | 0.282 | 0.242 | 0.281 | 0.277 | 0.288 | 0.325 | 0.290 | 0.290 | 0.324 | 0.309 |
| Central | Shanxi | 0.335 | 0.304 | 0.328 | 0.332 | 0.337 | 0.376 | 0.337 | 0.352 | 0.391 | 0.399 |
| | Jilin | 0.347 | 0.329 | 0.359 | 0.364 | 0.356 | 0.386 | 0.324 | 0.337 | 0.349 | 0.337 |
| | Heilongjiang | 0.351 | 0.340 | 0.347 | 0.354 | 0.344 | 0.377 | 0.323 | 0.328 | 0.353 | 0.355 |
| | Anhui | 0.433 | 0.399 | 0.428 | 0.438 | 0.455 | 0.502 | 0.470 | 0.484 | 0.502 | 0.502 |
| | Jiangxi | 0.401 | 0.368 | 0.400 | 0.405 | 0.417 | 0.457 | 0.426 | 0.435 | 0.455 | 0.462 |
| | Henan | 0.514 | 0.488 | 0.528 | 0.543 | 0.533 | 0.561 | 0.532 | 0.539 | 0.558 | 0.558 |
| | Hubei | 0.462 | 0.422 | 0.453 | 0.453 | 0.468 | 0.518 | 0.483 | 0.477 | 0.508 | 0.506 |
| | Hunan | 0.430 | 0.397 | 0.425 | 0.431 | 0.449 | 0.508 | 0.456 | 0.466 | 0.478 | 0.485 |
| Western | Inner Mongolia | 0.379 | 0.346 | 0.354 | 0.363 | 0.348 | 0.393 | 0.347 | 0.355 | 0.403 | 0.402 |
| | Guangxi | 0.363 | 0.331 | 0.362 | 0.374 | 0.378 | 0.417 | 0.382 | 0.390 | 0.407 | 0.406 |
| | Chongqing | 0.392 | 0.364 | 0.399 | 0.426 | 0.411 | 0.442 | 0.406 | 0.420 | 0.436 | 0.430 |
| | Sichuan | 0.440 | 0.398 | 0.433 | 0.441 | 0.443 | 0.492 | 0.459 | 0.469 | 0.482 | 0.496 |
| | Guizhou | 0.382 | 0.330 | 0.388 | 0.402 | 0.395 | 0.485 | 0.428 | 0.425 | 0.444 | 0.427 |
| | Yunnan | 0.356 | 0.322 | 0.354 | 0.358 | 0.368 | 0.415 | 0.385 | 0.394 | 0.414 | 0.417 |
| | Tibet | 0.280 | 0.228 | 0.257 | 0.277 | 0.279 | 0.392 | 0.307 | 0.285 | 0.291 | 0.274 |
| | Shaanxi | 0.384 | 0.351 | 0.373 | 0.376 | 0.385 | 0.422 | 0.386 | 0.387 | 0.409 | 0.424 |
| | Gansu | 0.282 | 0.275 | 0.277 | 0.293 | 0.277 | 0.327 | 0.277 | 0.284 | 0.326 | 0.317 |
| | Qinghai | 0.239 | 0.227 | 0.271 | 0.267 | 0.281 | 0.334 | 0.268 | 0.271 | 0.290 | 0.389 |
| | Ningxia | 0.275 | 0.229 | 0.253 | 0.259 | 0.255 | 0.306 | 0.267 | 0.266 | 0.313 | 0.299 |
| | Xinjiang | 0.308 | 0.268 | 0.287 | 0.315 | 0.315 | 0.364 | 0.311 | 0.312 | 0.358 | 0.347 |

Table 3. Coupling Coordination Degree of Producer Services and Manufacturing in China’s Provinces from 2013 to 2022.

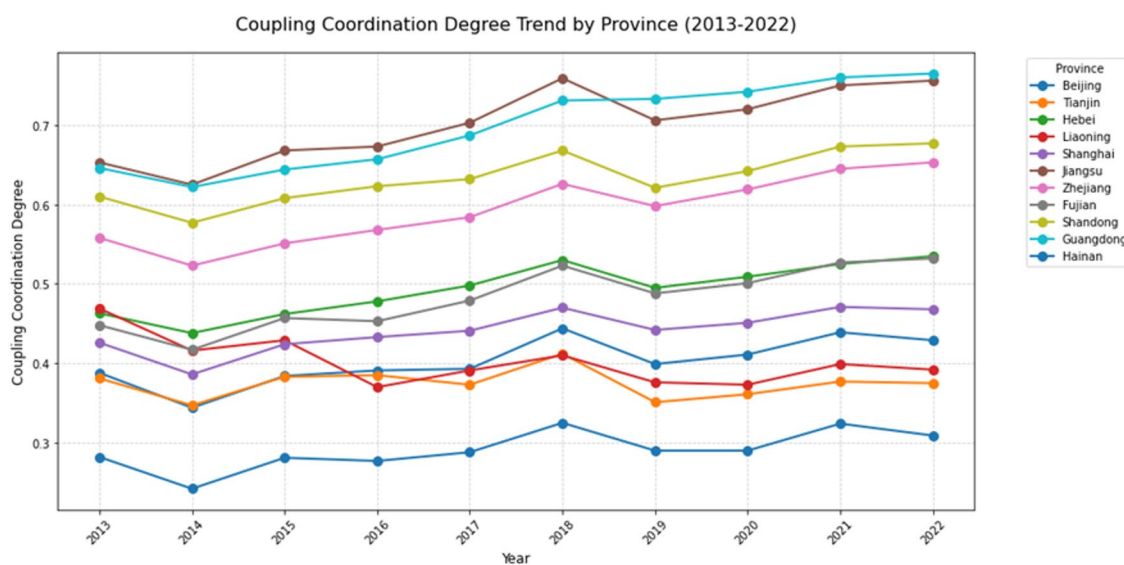


Fig. 1. Temporal trajectories of CCD (D) between producer services and manufacturing in Eastern China (11 provinces), 2013–2022.

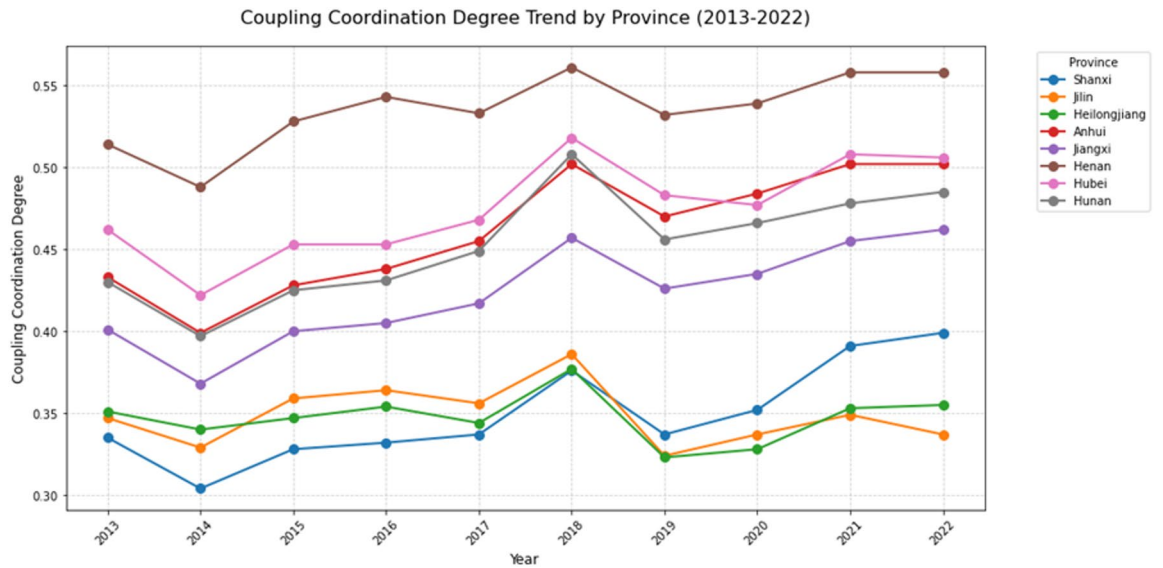


Fig. 2. Temporal trajectories of CCD (D) between producer services and manufacturing in Central China (8 provinces), 2013–2022.

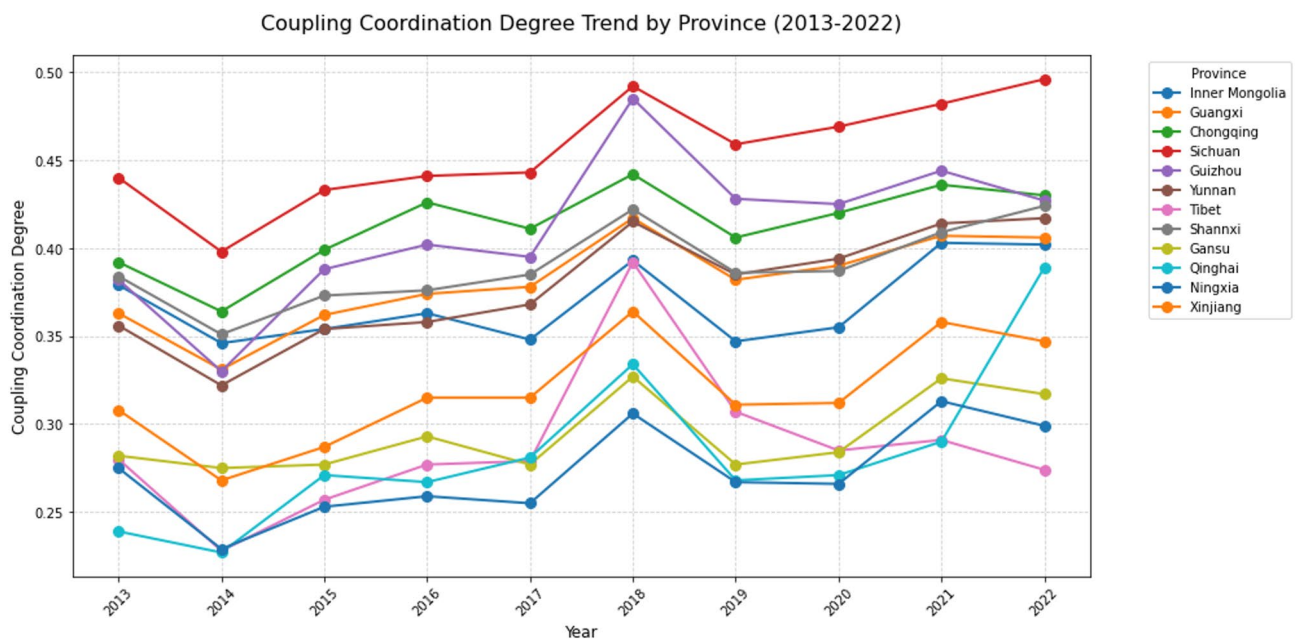


Fig. 3. Temporal trajectories of CCD (D) between producer services and manufacturing in Western China (12 provinces), 2013–2022.

with the observed gradient, and these potential channels are examined in Sect. 5. The regional gradient is also consistent with policy narratives emphasizing sustainability-oriented upgrading, while the present study focuses on CCD as an integration performance measure and does not directly evaluate environmental outcomes. These patterns motivate the subsequent spatial dependence analysis in Sect. 4, which examines spatial autocorrelation and local clustering of CCD across provinces.

Spatial and temporal distribution characteristics of the coupling coordination degree between producer services and manufacturing

Spatial autocorrelation test of CCD

To further examine the spatial dependence of CCD (D), we construct a spatial weight matrix (W) using a first-order Queen contiguity criterion. Specifically, $w_{pq} = 1$ when provinces p and q share a common boundary or vertex, and $w_{pq} = 0$ otherwise, with $w_{pp} = 0$. Compared with the Rook contiguity matrix, the Queen criterion

| Years | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|-----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Moran's I | 0.403 | 0.391 | 0.431 | 0.416 | 0.449 | 0.417 | 0.439 | 0.455 | 0.436 | 0.410 |
| E(I) | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 |
| SD(I) | 0.116 | 0.116 | 0.116 | 0.116 | 0.116 | 0.115 | 0.115 | 0.116 | 0.115 | 0.115 |
| Z | 3.734 | 3.663 | 4.008 | 3.881 | 4.168 | 3.886 | 4.089 | 4.222 | 4.070 | 3.826 |
| p-value* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Table 4. Global Moran's I for CCD(D) (2013–2022).

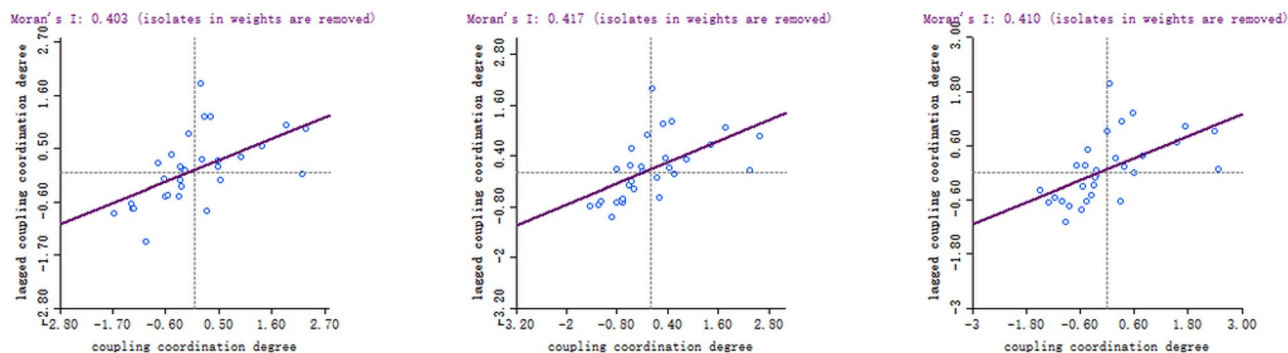


Fig. 4. Moran scatter plots of CCD (D) in 2013, 2018, and 2022 based on the first-order Queen contiguity weight matrix.

incorporates both edge- and vertex-based adjacency and therefore captures a broader set of geographically proximate linkages among provinces. We adopt a contiguity-based matrix because coordination spillovers between producer services and manufacturing are most likely transmitted through adjacent administrative units, including cross-border factor mobility, infrastructure connectivity, and policy diffusion. For comparability across provinces, the spatial weight matrix is row-standardized in the SDM estimation. The same first-order Queen contiguity specification is used consistently in the spatial dependence tests and the SDM estimation.

Based on W , we apply Global Moran's I to test the spatial autocorrelation of CCD (D). Moran's I evaluates whether provinces with similar CCD levels are spatially clustered. As reported in Table 4, Moran's I remains positive throughout 2013–2022 (0.391–0.455), indicating positive spatial autocorrelation in CCD. All Z-statistics exceed the 5% critical value of 1.96, and the corresponding p-values are $p < 0.001$, confirming statistically significant spatial dependence in CCD for each year. These results provide empirical motivation for the subsequent local spatial association analysis and support the use of spatial econometric models in the driver analysis.

Moran scatter plots of the coupling coordination degree between producer services and manufacturing

To complement the Global Moran's I results in Sect. 4.1, this study reports Moran scatter plots of CCD (D) for 2013, 2018, and 2022 in Fig. 4. These plots provide an intuitive visualization of spatial dependence by relating each province's CCD (D) to its spatially lagged value, thereby illustrating spatial association patterns that may not be fully conveyed by a single global statistic. In each Moran scatter plot, the horizontal axis is the standardized CCD (D), obtained by mean-centering and scaling by the standard deviation, and the vertical axis is the spatially lagged CCD (D) computed from the first-order Queen contiguity spatial weight matrix W described in Sect. 4.1. When computing the spatial lag, W is row-standardized so that each row sums to one. Observations in the high–high and low–low quadrants indicate positive spatial association, whereas observations in the low–high and high–low quadrants indicate potential local spatial outliers. Overall, the scatter plots are consistent with the significant Global Moran's I statistics reported above, suggesting that CCD (D) exhibits non-random spatial dependence across provinces.

In 2013, a large share of provinces locate in the high–high (HH) and low–low (LL) quadrants of the Moran scatter plot (21 out of 31, approximately 68%), suggesting that positive spatial association is prevalent. Points in the HH quadrant are mainly concentrated in the eastern coastal region, whereas points in the LL quadrant are largely observed in inland and northwestern areas. Only a small number of observations fall into the high–low (HL) and low–high (LH) quadrants, indicating potential local spatial outliers. This visual pattern is consistent with the positive and statistically significant Global Moran's I reported for 2013 in Table 4.

In 2018, the share of observations in the HH and LL quadrants remains similar (21 provinces, approximately 68%). The HH pattern continues to be more pronounced in the coastal region, while the LL pattern remains concentrated in inland and northwestern areas. A limited number of observations fall into the HL or LH quadrants, again suggesting potential local outliers. Overall, the 2018 scatter plot remains consistent with the significant Global Moran's I reported in Table 4.

In 2022, the proportion of observations in the HH and LL quadrants increases (24 provinces, approximately 77%), indicating a more consolidated spatial association pattern than in 2018. The HH quadrant continues to be dominated by eastern coastal provinces, while the LL quadrant remains concentrated in parts of inland and northwestern China. The number of observations in the HL/LH quadrants is small, implying that local deviations exist but are not dominant in the overall spatial pattern.

Overall, the Moran scatter plots suggest a stable coastal–inland contrast in CCD, characterized by persistent clustering of relatively high coordination levels in the eastern coastal region and relatively low coordination levels in parts of inland and northwestern China. This pattern is broadly consistent with recent evidence that linkages between manufacturing and producer services tend to exhibit stronger spatial clustering in eastern China, while corresponding patterns are weaker in many central and western settings⁵¹. In contrast, studies using distance-based spatial structures at finer spatial scales often report that spatial influence attenuates beyond a finite range, implying that the apparent strength of local association can vary with spatial scale and the specification of W ⁵².

Analysis of driving factors for the coupling and coordination degree between the producer services and manufacturing

Selection of driving factors

Prior studies identify multiple determinants of coordination between producer services and manufacturing, including economic development, transportation conditions, openness, labor quality, research and development capacity, capital accumulation, and human capital^{53–56}. Building on this evidence, this study develops a theory-integrated driver framework that links mechanisms to variable selection and to the spillover structure captured by the SDM.

The theoretical integration follows a unified logic. Complex adaptive systems thinking treats producer services and manufacturing as interdependent subsystems whose coordination emerges from feedback, adaptation, and matching between the two sectors. This implies that CCD (D) is shaped by both enabling conditions and the compatibility of sectoral upgrading paths. New structural economics explains how local endowments, structural transformation, and public goods provision influence coordination by reducing transaction costs and improving factor allocation. Evolutionary economic geography explains why coordination and its determinants may be spatially interdependent through path dependence, proximity-based externalities, and diffusion processes across provinces. Taken together, these perspectives imply that key drivers can operate through within-province channels and through spatial spillover channels. This implication motivates the SDM specification and the formulation of hypotheses on both direct effects and spillover effects.

Based on new structural economics, general public service expenditure (Ln GPSE) captures the enabling role of public investment and institutional support. Higher Ln GPSE is expected to improve the business environment and infrastructure conditions that facilitate producer services and manufacturing coordination. It can also strengthen governance capacity that supports productivity-enhancing upgrading under the relevant policy context^{57–60}. From an interprovincial perspective, Ln GPSE may generate spillovers through policy learning and demonstration effects in geographically proximate regions. The spillover channel is expected to be weaker than the direct channel because public goods provision is largely place-based.

Based on complex adaptive systems thinking, informatization level (IL) and labor force level (LFL) capture two core capacities that affect system adaptation and coordination efficiency. Higher IL is expected to improve connectivity, information processing, and coordination efficiency across production and service activities. It can also facilitate knowledge diffusion and cross-regional collaboration. A stronger labor force base can enhance absorptive capacity and improve the ability to integrate service inputs into manufacturing upgrading. Its effect can be positive when labor resources reflect skill-based upgrading and learning capacity. It can be negative when labor expansion mainly reflects low-end factor dependence and reinforces mismatched specialization^{61,62}.

Based on evolutionary economic geography, residents' income (Ln RHI) captures demand-side upgrading and market scale effects that can reshape demand for producer services and manufactured goods. Industrial structure (IS) reflects supply-side specialization and upgrading that may influence the matching relationship between the two sectors. Both drivers can operate through spatial spillovers because demand expansion, technology diffusion, and industrial reorganization often propagate through interprovincial networks and geographic proximity. Their net effects depend on whether structural upgrading strengthens complementary matching or induces structural mismatch between the two sectors^{63,64}. The “dual carbon” agenda provides policy context for interpreting upgrading-related channels and regionally differentiated implications^{65–70}.

Based on the above logic, five core explanatory variables are selected, namely Ln GPSE, Ln RHI, IS, IL, and LFL. Their definitions and symbols follow Table 5 to ensure consistency across descriptive statistics and model estimation. Given the statistically significant spatial dependence of CCD (D) in Sect. 4.1 (Table 4), we formulate testable hypotheses on both direct effects and spatial spillover effects before presenting model results.

H1. Ln GPSE is expected to have a positive direct effect on CCD (D) and a positive spatial spillover effect.

H2. Ln RHI is expected to have a positive direct effect on CCD (D) and a positive spatial spillover effect.

H3a. IS is expected to have a positive direct effect on CCD (D) and a positive spatial spillover effect when structural upgrading strengthens complementary matching between producer services and manufacturing.

H3b. IS is expected to have a negative direct effect on CCD (D) and a negative spatial spillover effect when structural upgrading induces structural mismatch.

H4. IL is expected to have a positive direct effect on CCD (D) and a positive spatial spillover effect.

| Variable names | Variable symbols | Sample size | Mean | Standard deviation | Minimum value | Maximum value |
|------------------------------------|------------------|-------------|-----------|--------------------|---------------|---------------|
| Coupling coordination degree | CCD | 310 | 0.4244032 | 0.1160923 | 0.227223 | 0.765379 |
| General public service expenditure | Ln GPSE | 310 | 6.038104 | 0.6486593 | 4.121943 | 7.544084 |
| Regional residents' income | Ln RHI | 310 | 10.12874 | 0.3956431 | 9.184694 | 11.28489 |
| Industrial structure | IS | 310 | 1.341525 | 0.7226276 | 0.572236 | 5.29682 |
| Informatization level | IL | 310 | 0.0656939 | 0.1423834 | 0.0152941 | 2.512909 |
| Labor force level | LFL | 310 | 7.480117 | 0.8997841 | 4.967031 | 8.839856 |

Table 5. Descriptive Statistics of Variables.

| | Test item | Test value | P value |
|---------------------------------------|-----------------|------------|---------|
| LM test | Moran's I | 1.733* | 0.083 |
| | LM-error | 47.227*** | 0.000 |
| | Robust LM-error | 56.967*** | 0.000 |
| | LM-lag | 2.861* | 0.091 |
| | Robust LM-lag | 12.600*** | 0.000 |
| LR test | LR-SDM/SEM | 36.48*** | 0.0000 |
| | LR-SDM/SAR | 30.22*** | 0.0000 |
| Wald test | Wald-SDM/SEM | 37.17*** | 0.0000 |
| | Wald-SDM/SAR | 31.14*** | 0.0000 |
| Test of Space-Time-Time Fixed Effects | LR-both/time | 711.42*** | 0.0000 |
| | LR-both/ind | 85.85*** | 0.0000 |

Table 6. Selection of Spatial Econometric Models. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

H5a. LFL is expected to have a positive direct effect on CCD (D) and a positive spatial spillover effect when labor resources primarily reflect skill-based upgrading and absorptive capacity.

H5b. LFL is expected to have a negative direct effect on CCD (D) and a negative spatial spillover effect when labor resources reinforce low-end factor dependence.

Descriptive statistics of variables

Using a balanced province–year panel of 31 provinces over 2013–2022 ($N = 310$), this section reports descriptive statistics for CCD (D) and the five driving factors used in the subsequent SDM analysis. Table 5 summarizes the mean, standard deviation, and minimum–maximum values for each variable. The average CCD (D) is 0.424 (0.227–0.765), indicating substantial variation across provinces and over time. Notably, IL exhibits the greatest dispersion among the driving factors, suggesting pronounced cross-regional heterogeneity in informatization. These statistics provide a foundation for estimating and interpreting direct and spatial spillover effects in Sect. 5.3.

Selection of spatial econometric models

To select an appropriate spatial panel specification for examining the relationship between CCD (D) and its driving factors, we follow standard model selection procedures, with the test results reported in Table 6. First, diagnostic tests indicate spatial dependence. Moran's I computed on the residuals of the non-spatial two-way fixed-effects panel model is significant at the 10% level ($z = 1.733$, $p = 0.083$), and the LM tests are also significant. Specifically, LM-error is significant at the 1% level ($p < 0.01$), and LM-lag is significant at the 10% level ($p = 0.091$). Both robust LM-error and robust LM-lag are significant ($p < 0.01$), indicating that a spatial econometric specification is necessary.

Second, the Wald test and Likelihood Ratio (LR) test are used to examine whether the SDM can be simplified to the Spatial Autoregressive model (SAR) or the Spatial Error model (SEM). Both LR and Wald tests reject the corresponding restrictions at the 1% level ($p < 0.01$), supporting SDM as an appropriate specification.

Third, the LR tests for fixed effects reject the absence of time fixed effects and province fixed effects at the 1% level ($p < 0.01$), supporting a two-way fixed-effects structure. Model selection between fixed and random effects in the Spatial Durbin framework relies on the Hausman test results. The Hausman test results are significant at the 1% significance level. Therefore, this paper ultimately selects the two-way fixed-effects SDM.

Analysis of regression results of SDM

Based on the two-way fixed-effects SDM estimates reported in Table 7, significant within-province effects and selective spatial spillovers are observed for CCD (D). For the local coefficients, Ln GPSE is positive and significant ($b = 0.0734$, $p < 0.001$), whereas IS ($b = -0.0139$, $p = 0.009$) and LFL ($b = -0.0342$, $p = 0.004$) are negative and significant. These negative coefficients may indicate that structural adjustment and the enabling conditions captured by IS and LFL do not fully translate into higher CCD (D) in this specification. In contrast,

| Variable Value | Regression Coefficient | Z Value | P Value |
|----------------|------------------------|---------|---------|
| Ln GPSE | 0.0733508*** | 7.13 | 0.000 |
| Ln RHI | -0.0244396 | -0.77 | 0.439 |
| IS | -0.0139339*** | -2.62 | 0.009 |
| IL | 0.000197 | 0.03 | 0.973 |
| LFL | -0.0341954*** | -2.90 | 0.004 |
| W × Ln GPSE | 0.0157114 | 0.79 | 0.431 |
| W × Ln RHI | 0.2454585*** | 4.90 | 0.000 |
| W × IS | -0.006643 | -0.60 | 0.546 |
| W × IL | 0.0280228** | 2.34 | 0.019 |
| W × LFL | -0.0021158 | -0.09 | 0.931 |
| Rho | 0.1626504** | 2.21 | 0.027 |
| Log-likelihood | 897.9722 | | |
| R ² | 0.2880 | | |

Table 7. Regression Results of the SDM. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| Variable | Direct Effect | Indirect Effect | Total Effect |
|----------|---------------|-----------------|--------------|
| Ln GPSE | 0.074712*** | 0.0321569* | 0.1068689*** |
| p-value | 0 | 0.087 | 0 |
| Ln RHI | 0.0325903 | 0.2894593*** | 0.3220496*** |
| p-value | 0.271 | 0 | 0 |
| IS | -0.0132594*** | 0.0047857 | -0.008474 |
| p-value | 0.009 | 0.7 | 0.538 |
| IL | 0.0012464 | 0.0335105** | 0.0347569** |
| p-value | 0.827 | 0.015 | 0.031 |
| LFL | -0.0347156*** | -0.008172 | -0.042888 |
| p-value | 0.002 | 0.77 | 0.146 |

Table 8. Results of Effect Decomposition of SDM. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Ln RHI ($b = -0.0244$, $p = 0.439$) and IL ($b = 0.000197$, $p = 0.973$) are not significant, suggesting that their within-province associations with CCD (D) are not supported.

Regarding spillovers, $W \times \text{Ln RHI}$ is positive and highly significant ($b = 0.2455$, $p < 0.001$), indicating that higher Ln RHI in neighboring provinces is associated with higher CCD (D) in the focal province. $W \times \text{IL}$ is also positive and significant ($b = 0.0280$, $p = 0.019$). In contrast, $W \times \text{Ln GPSE}$, $W \times \text{IS}$, and $W \times \text{LFL}$ are not significant ($p > 0.10$). Finally, the spatial autoregressive parameter ρ is positive and significant ($\rho = 0.1627$, $p = 0.027$), confirming positive spatial dependence in CCD (D). Because SDM coefficient estimates are not directly interpretable as marginal effects due to spatial feedback, Sect. 5.5 further reports direct and indirect effects.

Decomposition of SDM effects

Because the SDM includes spatial lags and feedback effects, regression coefficients alone do not represent marginal impacts. Following the partial-derivative approach proposed by LeSage and Pace⁷¹, we decompose the impacts of each driving factor into direct, indirect, and total effects. The direct effect captures the average within-province impact of a change in a driver on its own CCD (D) after accounting for spatial feedback. The indirect effect captures the average cross-province spillover transmitted through spatial linkages. The total effect is the sum of the direct and indirect effects. Table 8 reports the decomposition results.

Table 8 indicates heterogeneous impact channels across drivers. Ln GPSE shows a positive and significant direct effect (0.0747 , $p < 0.01$) and a weaker indirect effect (0.0322 , $p = 0.087$), yielding a positive and significant total effect (0.1069 , $p < 0.01$). Ln RHI exhibits a large and highly significant indirect effect (0.2895 , $p < 0.01$) and a significant total effect (0.3220 , $p < 0.01$), whereas its direct effect is not significant ($p = 0.271$), implying that residents' income operates primarily through spillovers. In practical terms, because Ln RHI is in logarithms, a 10% increase in residents' income in a province corresponds to an approximate 0.0289 increase in the average spillover component of CCD (D) across other provinces (0.2895×0.10). IL also shows a significant indirect effect (0.0335 , $p = 0.015$) and total effect (0.0348 , $p = 0.031$), but an insignificant direct effect ($p = 0.827$), suggesting that informatization contributes mainly via cross-regional transmission. By contrast, IS has a negative and significant direct effect (-0.0133 , $p = 0.009$) but insignificant indirect and total effects ($p = 0.700$ and $p = 0.538$), and LFL has a negative and significant direct effect (-0.0347 , $p = 0.002$) but insignificant indirect and total effects ($p = 0.770$).

| VARIABLES | (1) | (2) | (3) | (4) |
|--------------|---------|-----------|-----------|----------|
| | CCD (D) | CCD (D) | CCD (D) | CCD (D) |
| Ln GPSE | 0.040* | 0.084*** | | 0.094*** |
| | (1.90) | (5.69) | | (6.05) |
| Ln RHI | -0.039 | 0.091 | 0.082 | 0.056 |
| | (-0.38) | (1.25) | (1.19) | (0.74) |
| IS | -0.016* | -0.019*** | -0.020*** | -0.017** |
| | (-1.92) | (-3.11) | (-3.31) | (-2.59) |
| IL | 0.000 | -0.000 | -0.001 | 0.003 |
| | (0.19) | (-0.12) | (-0.50) | (1.23) |
| LFL | -0.009 | -0.027 | -0.022 | -0.030* |
| | (-0.44) | (-1.48) | (-1.27) | (-1.88) |
| X6 | | -0.298** | | |
| | | (-2.42) | | |
| L.Ln GPSE | | | 0.096*** | |
| | | | (6.25) | |
| Constant | 0.684 | -0.754 | -0.791 | -0.459 |
| | (0.59) | (-0.91) | (-1.06) | (-0.57) |
| Observations | 185 | 309 | 278 | 278 |
| R-squared | 0.990 | 0.985 | 0.987 | 0.987 |
| year FE | Yes | Yes | Yes | Yes |
| id FE | Yes | Yes | Yes | Yes |

Table 9. Results of the Robustness Test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, t-statistics are reported in parentheses. Year fixed effects and province fixed effects are included in all specifications. R-squared refers to the within R-squared.

and $p = 0.146$). Overall, spillovers are concentrated in Ln RHI and IL, while Ln GPSE is dominated by within-province effects.

Robustness test

To assess the robustness of the baseline findings, we implement several alternative specifications, with results reported in Table 9. The key inferences remain qualitatively stable across these checks, suggesting that the baseline conclusions are not driven by sample selection, omitted fiscal-cost factors, or endogeneity concerns related to reverse causality and contemporaneous feedback.

First, we shorten the sample period by excluding observations from 2013 to 2016 and re-estimate the model using the 2017 to 2022 subsample (Column (1)). The coefficients on Ln GPSE and IS retain the same signs and remain statistically significant, indicating that the baseline results are not driven by early-period observations.

Second, we add an additional control variable, the tax burden level (X6), to account for fiscal and cost-related constraints (Column (2)). The coefficient on X6 is negative and statistically significant, implying that a heavier tax burden is associated with lower CCD (D). This pattern is consistent with the view that stronger fiscal-cost pressure can weaken incentives and capacity for producer services-manufacturing integration. Importantly, after controlling for X6, the estimated effects of the key explanatory variables remain qualitatively unchanged.

Third, we conduct lag-based specifications to strengthen temporal ordering and mitigate concerns about reverse causality (Columns (3) and (4)). In Column (3), the one-period lag of public service expenditure remains positive and statistically significant, and the main coefficients preserve similar signs in the alternative lag specification (Column (4)). Overall, Table 9 indicates that the main results are robust to alternative sample windows, the inclusion of an additional fiscal-cost control, and lag-based specifications.

Discussion and implications

Analysis of research conclusions

Using provincial panel data for 31 provinces in China from 2013 to 2022, this study integrates the CCD framework with the SDM to examine the spatiotemporal evolution and spatial spillovers of coordination between producer services and manufacturing. This section interprets the main empirical patterns by linking mechanisms, regional heterogeneity, and spatial interdependence to the theory-integrated framework. In particular, a complex adaptive systems perspective treats coordination as a system-level outcome that depends on subsystem matching and adaptation. A new structural economics perspective highlights local enabling conditions for structural transformation. An evolutionary economic geography perspective emphasizes proximity-based externalities, diffusion, and cumulative processes that shape spatial dependence and spillovers.

First, CCD increases steadily over time, yet the overall level remains relatively low-to-medium in most provinces. From a complex adaptive systems perspective, this pattern implies that improvements in the two subsystems do not automatically translate into high coordination because coordination depends on the compatibility of their co-evolution. Upgrading in producer services and transformation in manufacturing may

not proceed synchronously, and matching between specialized service supply and manufacturing demand remains incomplete in many regions. Xu et al. similarly emphasize that coordinated development between manufacturing and related service sectors tends to improve gradually and requires structural adjustment before it translates into stronger system-level performance⁷².

Second, CCD exhibits a persistent regional gradient, with eastern provinces generally maintaining higher levels and faster improvement than central and western provinces. This pattern is consistent with a new structural economics interpretation that provinces differ in endowments and enabling capacity, and that these differences shape the feasibility and speed of structural transformation and sectoral coordination. At the same time, evolutionary economic geography implies that such regional differences can be reinforced through cumulative processes in which early advantages attract further resources and linkages. The gradient remains stable even when spatial dependence is explicitly modeled, implying that differences in development foundations and interprovincial connectivity continue to shape coordination trajectories. Li and Liu provide related evidence that collaborative agglomeration can generate spatial spillovers and uneven regional payoffs, which is consistent with a cumulative-advantage mechanism in more developed regions⁷³.

Third, CCD exhibits significant spatial dependence and stable local clustering. Moran's *I* remains positive and statistically significant throughout the sample period, indicating persistent positive spatial autocorrelation. LISA patterns reveal a clear geographic structure in which high-CCD provinces cluster near each other and low-CCD provinces also cluster near each other. From an evolutionary economic geography perspective, these patterns are consistent with proximity-based externalities and diffusion. They also align with a complex adaptive systems interpretation that coordination can propagate through interprovincial interactions rather than evolving as isolated provincial dynamics. The cluster membership of some provinces changes over time, which is consistent with neighborhood effects and diffusion dynamics. Gong et al. report spatial evidence that producer services agglomeration is associated with clustered patterns and neighborhood diffusion, supporting the interpretation that coordination behaves as a regional system outcome shaped by proximity and interprovincial interactions⁷⁴.

Fourth, the effect decomposition shows that determinants operate through differentiated channels, and the distinction between within-province effects and spillover effects is central for interpretation. This finding fits the integrated theory. New structural economics emphasizes that local public goods provision and institutional support reduce transaction costs and strengthen the local enabling environment, which is consistent with the result that public service expenditure improves coordination primarily through within-province effects. Complex adaptive systems implies that improved local enabling conditions can increase subsystem adaptability and strengthen local matching between producer services and manufacturing. In contrast, evolutionary economic geography implies that demand capacity and digital connectivity are more likely to transmit across provinces through market linkages, information flows, and network externalities, which is consistent with the result that residents' income and informatization mainly improve coordination through spillover effects. This study contributes by demonstrating that spillover-dominant drivers and locally dominant drivers can coexist in the same system, which has direct implications for policy design. Zhao and Yan provide supporting evidence that public fiscal expenditure can promote industrial transformation and upgrading⁷⁵, while Lu and Zhu provide evidence consistent with interprovincial externalities associated with digital development⁷⁶. The decomposition results indicate that the within-province component of public service expenditure is larger than its spillover component, whereas residents' income and informatization are dominated by spillover components.

Fifth, the main conclusions remain stable across robustness checks. The direction and significance patterns of key relationships are broadly unchanged under alternative specifications, including adjustments to the sample window and additional controls related to fiscal burden. This strengthens confidence that the identified channels reflect systematic spatial mechanisms associated with diffusion and interdependence emphasized by evolutionary economic geography, rather than specification-driven artifacts.

Overall, the evidence indicates that coordination between producer services and manufacturing in China is improving but remains uneven across space. It also shows that coordination dynamics are jointly shaped by local enabling capacity emphasized by new structural economics and interprovincial spillover mechanisms emphasized by evolutionary economic geography, while a complex adaptive systems perspective provides the system-level logic linking these forces to CCD outcomes. This provides a direct basis for the theoretical and policy implications developed in the following subsection.

Theoretical contributions and practical implications

This study makes three theoretical contributions to research on industrial integration and coordinated development.

First, it advances coupling coordination research by moving beyond measurement and descriptive comparison toward mechanism identification. By integrating the CCD framework with SDM and effect decomposition, the study explains why coordination differs across provinces and shows how interprovincial linkages shape these differences. This contributes to a mechanism-oriented understanding in which coordination is an emergent system outcome that depends on enabling conditions and cross-regional interactions, rather than a simple aggregation of sectoral performance.

Second, it demonstrates that coordination between producer services and manufacturing is governed by spatial interdependence rather than isolated provincial dynamics. Significant spatial dependence and spillover mechanisms indicate that coordination outcomes are jointly produced through interprovincial linkages. The evidence supports an interpretation in which diffusion, network externalities, and cumulative processes allow neighboring provinces to reinforce or constrain each other, which helps explain persistent clustering and uneven regional trajectories.

Third, it clarifies heterogeneous transmission channels by distinguishing within-province effects from spillover effects for key determinants. The evidence indicates that public service expenditure mainly operates

through within-province effects, whereas residents' income and informatization mainly operate through spillover effects. Industrial structure and labor force level are associated with negative within-province effects in the baseline estimates. This channel-based explanation refines the view that determinants are uniformly enabling or constraining. It highlights that determinants can matter through different pathways at local and interprovincial levels, and that structural change and factor allocation can either strengthen matching between the two sectors or intensify mismatch.

The results also suggest that firms may strengthen integration by deepening service embedding and by building collaboration capabilities that operate across provincial borders. Micro-level validation is needed to translate macro-level evidence into firm-level prescriptions. Manufacturing firms may deepen integration with producer services by promoting service-oriented upgrading, including stronger engagement with design services, R&D services, and after-sales solutions. They can also adopt digital tools that improve supply chain visibility, coordination efficiency, and interprovincial collaboration. Producer services firms may enhance integration by developing standardized and scalable offerings, such as testing and certification services, supply chain management services, and digital logistics solutions. These offerings can reduce coordination costs for manufacturing clients and facilitate the diffusion of coordination benefits across regions when interprovincial connectivity is strong.

Policy design should match the dominant channel through which each determinant operates. An approach limited to a single province is insufficient when spillover effects are strong.

First, because public service expenditure operates mainly through within-province effects, provincial governments can improve coordination by upgrading the structure and efficiency of public service provision that supports integration between producer services and manufacturing. Priorities include improving infrastructure and the business environment for service-oriented manufacturing, strengthening public platforms for testing and certification and for supply chain coordination, and using fiscal instruments such as dedicated funds, tax incentives, and government procurement to reduce coordination costs.

Second, because informatization mainly improves coordination through spillover effects, digital cooperation should be organized as interprovincial programs rather than isolated local investment. Regions can jointly deploy industrial internet connectivity across provincial borders, establish interoperable data standards and shared governance rules, and build interprovincial platforms for logistics scheduling, supply chain collaboration, and digital service outsourcing.

Third, because residents' income mainly operates through spillover effects, policies should emphasize market integration and demand diffusion. Regions can strengthen interprovincial trade and logistics networks and reduce transaction frictions so that demand expansion in one province can transmit to neighboring provinces through trade and mobility channels.

Fourth, because industrial structure and labor force level show negative within-province effects in the baseline estimates, structural upgrading and labor allocation should prioritize matching quality rather than expansion scale. Regions should reduce dependence on low-value-added segments and promote complementary matching between producer services and manufacturing. This includes guiding manufacturing upgrading toward service-driven pathways and implementing skills-oriented strategies that strengthen digital and sustainability-relevant competencies to reduce mismatch under the current policy context.

Taken together, the evidence supports a dual strategy. Provinces should strengthen local foundations through effective public services and institutional support. They should also activate interprovincial linkages through digital connectivity and market integration. This combination is particularly important for lagging regions, where cooperation and spillovers can accelerate coordination more feasibly than internal accumulation alone.

Research limitations and future directions

Although this study provides evidence on the spatiotemporal evolution and spatial spillovers of the coupling coordination degree between producer services and manufacturing, several limitations should be acknowledged. These limitations also indicate clear directions for future research.

First, the findings may be sensitive to the specification of the spatial weight matrix. The baseline model adopts a queen contiguity matrix to represent geographic adjacency, which is consistent with spatial diffusion based on proximity. However, geographic adjacency may not fully capture interprovincial economic linkages, such as trade connections, supply chain dependence, population mobility, and digital connectivity. Future studies can compare results under alternative spatial structures, including inverse distance matrices, *k*-nearest-neighbor matrices, and matrices constructed from economic distance or trade intensity, to assess whether the within-province effects and spillover effects remain stable under different interprovincial linkage assumptions.

Second, the measurement of coordinated development has inherent constraints. The coupling coordination degree is a composite index that depends on the indicator system and the weighting scheme. More importantly, it captures the level of coordination but does not directly identify the direction of imbalance. It cannot indicate whether coordination is constrained primarily by lagging producer services, lagging manufacturing, or asymmetric upgrading between the two subsystems. Future research can supplement the coupling coordination degree with imbalance diagnostics that explicitly distinguish leading and lagging subsystems, and then examine whether different imbalance patterns correspond to different drivers and policy priorities.

Third, the set of explanatory variables is necessarily incomplete. The current model focuses on public service expenditure, residents' income, informatization, industrial structure, and labor force level. Other determinants that plausibly affect coordinated development, such as environmental regulation intensity, regional innovation capacity, green technology adoption, and institutional quality, are not explicitly incorporated in the baseline specification. Future studies can integrate such variables to enrich mechanism explanations and reduce the risk of omitted-variable bias.

Fourth, the use of provincial-level data may mask within-province heterogeneity and micro-level mechanisms. Provincial indicators capture macro coordination outcomes but cannot reveal how cities, industries, and firms interact to generate these outcomes or transmit spillovers. Future research can use city-level, industry-level, or firm-level datasets to explore micro-level mechanisms, including service-oriented manufacturing practices, platform-based producer services, and firm network channels through which spillover effects propagate. Multi-level designs may also help distinguish local upgrading processes from network-driven diffusion.

Fifth, coordination and spillovers may evolve dynamically and may be influenced by policy shocks and path dependence. The SDM provides a useful benchmark, but it may not fully capture lagged adjustment, nonlinear responses, or policy-driven changes in coordination dynamics. Future work can adopt dynamic spatial panel models, test threshold effects such as whether informatization spillovers strengthen after digital infrastructure reaches a certain level, and conduct policy-oriented analyses around major national initiatives to better characterize long-run coordination processes.

In summary, future research can extend this study through three priority avenues. The first is to strengthen sensitivity checks on spatial structures by testing alternative weight matrices that reflect economic and network linkages. The second is to move to finer-grained data and multi-level designs to uncover micro-level mechanisms and identify the direction of imbalance between the two subsystems. A further extension is to strengthen the environmental dimension by incorporating explicit environmental performance indicators, such as carbon intensity, energy efficiency, pollution emissions, or green total factor productivity, and by examining whether coordination is associated with these outcomes through mechanisms such as green innovation and green technology adoption. This remains outside the measurement scope of the current study and is proposed as future work.

Data availability

The data presented in this study are available on request from the corresponding author.

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References

- Lin, B. & Xie, J. Does environmental regulation promote industrial structure optimization in China? A perspective of technical and capital barriers. *Environ. Impact Assess. Rev.* **98**, 106971 (2023).
- Zhang, Y. & Dilanchiev, A. Economic recovery, industrial structure and natural resource utilization efficiency in China: Effect on green economic recovery. *Resour. Policy* **79**, 102958 (2022).
- Zhao, J., Jiang, Q., Dong, X., Dong, K. & Jiang, H. How does industrial structure adjustment reduce CO₂ emissions? Spatial and mediation effects analysis for China. *Energy Econ.* **105**, 105704 (2022).
- Peng, D., Elahi, E. & Khalid, Z. Productive service agglomeration, human capital level, and urban economic performance. *Sustainability* **15**, 7051 (2023).
- Yu, C., Tang, D., Tenkorang, A. P. & Bethel, B. J. The impact of the opening of producer services on the international competitiveness of manufacturing industry. *Sustainability* **13**, 11224 (2021).
- Chen, S. & Zhang, H. Does digital finance promote manufacturing servitization: Micro evidence from China. *Int. Rev. Econ. Finance.* **76**, 856–869 (2021).
- Zhang, R. & Liu, M. Industrial collaborative agglomeration, industrial coupling coordination and high-quality economic development. *J. Commercial Econ.* <https://doi.org/10.13902/j.cnki.syyj.2022.06.010> (2022).
- Lai, Z., Wang, B. & He, X. Research on the digital transformation of producer services to drive manufacturing technology innovation. *Sustainability* **15**, 3784 (2023).
- Xiao, W. & Fan, D. The “simultaneous development of quantity and quality”: Research on the impact of the digital economy in enabling manufacturing innovation. *Systems* **12**, 470 (2024).
- Zhao, X. Evaluation of industrial linkage between producer services and manufacturing in China: Analysis and comparison based on the international input-output model. *Acad. Exch.* **5**, 97–112 (2024).
- Xi, J. *Hold High the Great Banner of Socialism with Chinese Characteristics and Strive in Unity to Build a Modern Socialist Country in All Respects: Report to the 20th National Congress of the Communist Party of China* (People's Publishing House, Beijing, 2022).
- Zhang, H. & Zhang, C. Identification on the common supply chain paths of CO₂ and NO_x emissions from the manufacturing industry in China. *Appl. Econ.* **57**, 1297–1313 (2025).
- Zhang, A., Zhang, W. & Guo, X. The digital economy, integration of productive services and manufacturing, and high-quality development of the manufacturing sector: Evidence from China. *Sustainability* **16**, 10258 (2024).
- Han, D. The growth of service sectors, institutional environment and quality development in China's manufacturing. *Systems* **11**, 128 (2023).
- Guerrieri, P. & Meliciani, V. Technology and international competitiveness: The interdependence between manufacturing and producer services. *Struct. Change Econ. Dyn.* **16**, 489–502 (2005).
- Sun, Z. & Liu, Y. Does industrial agglomeration promote carbon efficiency? A spatial econometric analysis and fractional-order grey forecasting. *J. Math.* **2021**, 1–18 (2021).
- Liu, B., Zheng, K., Zhu, M., Wu, F. & Zhao, X. Towards sustainability: The impact of industrial synergistic agglomeration on the efficiency of regional green development. *Environ. Sci. Pollut. Res.* **30**, 85415–85427 (2023).
- Gao, J. & Li, X. Theoretical and empirical study on the interactive mechanism between producer services and manufacturing. *China Ind. Econ.* **6**, 151–160. <https://doi.org/10.19581/j.cnki.ciejournal.2011.06.015> (2011).
- Song, X. M., Di Benedetto, C. A. & Zhao, Y. L. Pioneering advantages in manufacturing and service industries: Empirical evidence from nine countries. *Strateg. Manag. J.* **20**, 811–835 (1999).
- Dai, Y. How does synergistic agglomeration of productive service industry and manufacturing industry promote regional innovation. *Acad. J. Bus. Manage.* <https://doi.org/10.25236/AJBM.2021.030605> (2021).
- Chen, X. & Ma, G. Study on the characteristics and synergistic effects of industrial complex networks: Empirical evidence from Chinese manufacturing. *Kybernetes* **54**, 1373–1394. <https://doi.org/10.1108/K-09-2023-1771> (2025).
- Vilpoux, O. F., Gonzaga, J. F. & Pereira, M. W. G. Agrarian reform in the Brazilian Midwest: Difficulties of modernization via conventional or organic production systems. *Land Use Policy* **103**, 105327 (2021).
- Li, L., Li, G., Ozturk, I. & Ullah, S. Green innovation and environmental sustainability: Do clean energy investment and education matter?. *Energy Environ.* **34**, 2705–2720 (2023).

24. Ye, P., Li, J., Ma, W. & Zhang, H. Impact of collaborative agglomeration of manufacturing and producer services on air quality: Evidence from the emission reduction of PM_{2.5}, NO_x and SO₂ in China. *Atmosphere* **13**, 966 (2022).
25. Zhao, C., Liu, S. & Li, Z. Opening up of producer services and green development of manufacturing enterprises. *Contemp. Finance Econ.* <https://doi.org/10.13676/j.cnki.cn36-1030/f.20231129.002> (2024).
26. Wang, Y., Liu, J., Zhao, Z., Ren, J. & Chen, X. Research on carbon emission reduction effect of China's regional digital trade under the "double carbon" target: Combination of the regulatory role of industrial agglomeration and carbon emissions trading mechanism. *J. Clean. Prod.* **405**, 137049 (2023).
27. Wu, B. & Xu, Y. Towards sustainable development: Can industrial collaborative agglomeration become an accelerator for green and low-carbon transformation of resource-based cities in China? *J. Environ. Manage.* **381**, 125199 (2025).
28. Xie, X. & Guo, K. How does productive service agglomeration promote manufacturing servitisation from an innovation perspective?. *Int. Rev. Financ. Anal.* **92**, 103091 (2024).
29. Ni, Y. & Sun, J. Digital transformation and the development of servitized manufacturing in China: An asset specificity perspective. *Fin. Res. Lett.* **85**, 108039. <https://doi.org/10.1016/j.frl.2025.108039> (2025).
30. Cheng, Z. & Xu, C. The impact of digital economy on the deep integration of manufacturing and productive service industries. *Mod. Finance Econ.* **44**, 18–35 (2024).
31. Ding, J., Liu, B. & Shao, X. Spatial effects of industrial synergistic agglomeration and regional green development efficiency: Evidence from China. *Energy Econ.* **112**, 106156 (2022).
32. Xu, B. & Sun, Y. The impact of industrial agglomeration on urban land green use efficiency and its spatio-temporal pattern: Evidence from 283 cities in China. *Land* **12**, 824 (2023).
33. He, W. et al. Will green technological progress help industrial collaborative agglomeration increase regional carbon productivity: Evidence from Yangtze River Delta urban agglomerations. *Environ. Dev. Sustain.* **26**, 26019–26046 (2023).
34. Li, L., Arip, M. A. & Hong, P. C. Spatiotemporal evolution patterns of the coupling of carbon productivity and high-quality economic development in China. *Sci. Rep.* **15**, 9114 (2025).
35. Su, J., Shen, T. & Jin, S. Ecological efficiency evaluation and driving factor analysis of the coupling coordination of the logistics industry and manufacturing industry. *Environ. Sci. Pollut. Res.* **29**, 62458–62474 (2022).
36. Tian, Y. & Zhou, Y. Coupling coordination of digital village construction and high-quality agricultural development in China. *PLoS One* **20**, e0319090 (2025).
37. Gao, F., Li, Y., Wen, Y., Yang, X. & Cao, H. Research on the coordinated distribution and influencing factors of water-energy-food coupling. *Water Sav. Irrig.* **12**, 1–11 (2024).
38. Zhou, L. Research on the coupling coordination between green finance and digital economy: An empirical analysis of the Yangtze River Delta region. *China Circulation Econ.* <https://doi.org/10.16834/j.cnki.issn1009-5292.2024.11.022> (2024).
39. Xue, Z. The impact of pilot free trade zones on the agglomeration of regional producer services: Empirical evidence from Shanghai, Tianjin, Fujian, and Guangdong. *Enterp. Econ.* **43**, 25–35 (2024).
40. Huang, S., Ye, W. & Han, F. Does the digital economy promote industrial collaboration and agglomeration? Evidence from 286 cities in China. *Sustainability* **15**, 14545 (2023).
41. Li, N. & Wu, S. FDI embeddedness and the cross-regional evolution of manufacturing agglomeration production networks. *J. Invest. Res.* **38**, 4–15 (2019).
42. Tang, X., Zhang, X. & Li, Y. Dynamic coordination development in China's manufacturing and manufacturing-related service industries. *Econ. Res. J.* **53**, 79–93 (2018).
43. Liu, W., Bian, S. & Han, M. Analysis on the influencing factors of integrated development of manufacturing and producer services in Anhui Province. *J. Anhui Agric. Univ.* **31**, 55–60 (2022).
44. Yang, Y., Yuan, X., Ma, C., Xu, H. & Ren, C. Coupling coordination analysis of farmers' livelihoods and rural development in the Qinling–Daba Mountains: A case study of Luonan County in Shaanxi Province. *J. Ecol. Rural Environ.* **37**, 448–455 (2021).
45. Zhou, D. & Zhou, M. Differences in the coupling level of human capital and economic growth and the coupling path in five major urban agglomerations. *Stat. Decis.* **36**, 67–71 (2020).
46. Li, C. & Zhou, Y. Research on the spatio-temporal coupling relationship between agricultural water resources vulnerability and food security in China's main grain producing areas. *J. Ecol. Rural Environ.* **38**, 722–732 (2022).
47. Cheng, C. F. C. et al. Global inclusive and sustainable competitive industrial performance (ISCIP): An efficiency based spatio-temporal analysis for 139 countries. *Appl. Energy* **333**, 120603 (2023).
48. Cruz, M. D. Labor productivity, real wages, and employment in OECD economies. *Struct. Change Econ. Dyn.* **66**, 367–382 (2023).
49. Yao, Y., Cai, W., Zhou, Z. & Zheng, Y. Integration of manufacturing and services: Examining its effect on resource allocation and manufacturing labor productivity. *Int. Rev. Financ. Anal.* **96**, 103708 (2024).
50. Anouze, A. L., Lu, C. & Emrouznejad, A. Redefining competitive industrial performance indicator: A multiplicative data envelopment analysis approach. *J. Oper. Res. Soc.* <https://doi.org/10.1080/01605682.2025.2554746> (2025).
51. He, Y. & Zheng, H. How does environmental regulation affect industrial structure upgrading? Evidence from prefecture-level cities in China. *J. Environ. Manage.* **331**, 117267 (2023).
52. Zhang, X., He, S. & Ma, L. Local environmental fiscal expenditures, industrial structure upgrading, and carbon emission intensity. *Front. Environ. Sci.* **12**, 1369056. <https://doi.org/10.3389/fenvs.2024.1369056> (2024).
53. Wang, X., Ye, T. & Li, L. Coupling coordination and influencing factors of high-tech manufacturing and producer service industry: Empirical evidence from the three major urban agglomerations. *J. Capital Univ. Econ. Bus.* **23**, 26–42 (2021).
54. Chen, W., Han, C. & Guo, K. Research on coordinated development of productive-service industry and manufacturing industry in Xinjiang. *Sci. Technol. Manage. Res.* **35**, 115–118 (2015).
55. Herrero, D. & Rial, A. Labor costs, KIBS, and export performance: A comparative analysis of Germany and Mediterranean economies. *Struct. Change Econ. Dyn.* **65**, 184–198 (2023).
56. Bilenko, Y. Labor productivity in the agriculture, structural shifts and economic growth in the Central and Eastern European countries. *Agricultural Resource Economics: Int. Sci. E-J.* <https://doi.org/10.22004/ag.econ.330349> (2022).
57. Lin, Y., Chen, C. & Fu, C. New quality productive forces: From the perspective of new structural economics. *Acad. Forum.* **48**, 1–12 (2025).
58. Lin, J. Y. Industrial policies for avoiding the middle-income trap: A new structural economics perspective. *J. Chin. Econ. Bus. Stud.* **15**, 5–18 (2017).
59. Zhou, F. & Wang, X. The carbon emissions trading scheme and green technology innovation in China: A new structural economics perspective. *Econ. Anal. Policy* **74**, 365–381 (2022).
60. Shao, Z. & Dou, L. How can environmental degradation and income disparities influence national health: An "eye bird view" on China's provinces. *Front. Public Health* **11**, 1094775. <https://doi.org/10.3389/fpubh.2023.1094775> (2023).
61. Yin, M. & Xu, J. Characterization and grouping analysis of economic resilience of county-level cities in Jiangsu Province from the perspective of complex adaptive systems. *Trop. Geogr.* **44**, 2001–2014 (2024).
62. He, C. et al. Evaluation of urban resilience of China's three major urban agglomerations using complex adaptive system theory. *Sustainability* **15**, 14537 (2023).
63. Xu, J., Zhang, H., Chen, Y., Du, Z. & Ye, Y. The sequence of theoretical development and research agendas of evolutionary economic geography. *Geogr. Res.* **42**, 2433–2450 (2023).
64. Martin, R. & Sunley, P. Path dependence and regional economic evolution. *J. Econ. Geogr.* **6**, 395–437. <https://doi.org/10.1093/jeg/lbl012> (2006).

65. Tang, C., Xu, Y., Hao, Y., Wu, H. & Xue, Y. What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. *Energy Econ.* **103**, 105576 (2021).
66. Li, C., Solangi, Y. A. & Ali, S. Evaluating the factors of green finance to achieve carbon peak and carbon neutrality targets in China: A Delphi and fuzzy AHP approach. *Sustainability* **15**, 2721 (2023).
67. Cheng, M., Wang, J., Yang, S. & Li, Q. The driving effect of technological innovation on green development: From the perspective of efficiency. *Energy Policy* **188**, 114089 (2024).
68. Cao, J. et al. Impact of financial development and technological innovation on the volatility of green growth—evidence from China. *Environ. Sci. Pollut. Res.* **28**, 48053–48069 (2021).
69. Deng, H., Zheng, W., Shen, Z. & Štreimikiene, D. Does fiscal expenditure promote green agricultural productivity gains: An investigation on corn production. *Appl. Energy* **334**, 120666 (2023).
70. Song, W. & Tang, S. Does the digital economy really help reduce industrial carbon intensity? Empirical evidence from intermediate inputs of digital products in China. *Environ. Sci. Pollut. Res.* **31**, 56042–56055 (2024).
71. LeSage, J. & Pace, R. K. *Introduction to Spatial Econometrics* (Chapman and Hall/CRC, 2009). <https://doi.org/10.1201/9781420064254>.
72. Xu, Y., Li, J., Yan, Y., Gao, P. & Xie, H. Can coordinated development of manufacturing and information communication service industries boost economic resilience? An empirical study based on China's provinces. *Sustainability* **14**, 10758 (2022).
73. Li, X. & Liu, Y. The economic spillover effect of the collaborative agglomeration between manufacturing and producer services. *Sustainability* **16**, 5343 (2024).
74. Gong, W., Wang, C., Men, D., Zhang, M. & Wang, J. The influence and spatial spillover effects of producer services agglomeration on urban green development in China. *PLoS One* **19**, e0315870 (2024).
75. Zhao, J. & Yan, J. The impact of public fiscal expenditure on industrial transformation and upgrading: An inverted U-shape evidence from China. *Heliyon* **10**, e38456 (2024).
76. Lu, Y. & Zhu, S. Digital economy, scientific and technological innovation, and high-quality economic development: A mediating effect model based on the spatial perspective. *PLoS One* **17**, e0277245. <https://doi.org/10.1371/journal.pone.0277245> (2022).

Author contributions

X.Z. supervised this work, conducted the investigation, and wrote the manuscript. Q.X. contributed to data collection and processing and model analysis, and supported manuscript revision. T.Z. performed data curation and model analysis, and drafted the original manuscript. L.H. provided resources and contributed to writing, review, and editing.

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Declarations

Competing interests

The authors declare no competing interests.

Informed consent

Not applicable.

Institutional review board statement

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Additional information

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