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The Spatial Effect of Digital Economy Enabling Common Prosperity—An Empirical Study of the Yellow River Basin

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Abstract: The digital economy enhances economic efficiency and improves economic structure, driving economic growth through transformations in efficiency, momentum, and quality. It has become a new driving force for advancing common prosperity. This study uses SDM, SDID, and SPSTR models to explore the impact of digital economy on common prosperity, which constructs the index system to evaluate the common prosperity from process index and outcome index. According to the panel data of 76 cities in the Yellow River Basin from 2011 to 2021, and the findings are as follows: (1) The digital economy exhibits a development pattern characterized by high activity downstream and lower activity upstream, and the development trend is stable. The development pattern of common prosperity has changed from sporadic distribution to regional agglomeration, and the level of common prosperity in most cities has improved. (2) The digital economy has a significant positive spatial effect on common prosperity. And the findings are robust after introducing the "Big Data" exogenous policy impact, dynamic SDM model, and other methods. Moreover, spatial heterogeneity exists. The promotion effect in the upper and lower reaches is stronger, while the middle reaches are weakly affected by the digital economy. (3) The spatial spillover effect of the digital economy on common prosperity has a boundary, and the positive spillover reaches a maximum value at 600–650 km. (4) Nonlinear analysis confirms that the digital economy provides momentum for common prosperity industrial structure optimization that can effectively stimulate the "endogenous" growth mechanism, strengthen the marginal increasing effect of the digital economy driving common prosperity and enhance the effect of "making a bigger pie". The digital economy makes effective use of digital resources and technologies, promotes the equalization of public services, exerts a positive impact on the realization of common prosperity, and consolidates the effect of "dividing a better cake".

Keywords: digital economy; common prosperity; SDID model; SPSTR model; spatial spillover

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1. Introduction

The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China (CPC) called for "more significant and substantive progress in achieving common prosperity (CMP) for all people". The realization of CMP raises the question of how it can be achieved. The White Paper on Digital Ecology Industry Promoting CMP suggests that "one feasible pathway to achieving CMP is through the development of digital economy (DGE)". The DGE, driven by digital technology, facilitates the digital transformation and high-quality development of the global economy through three pathways: empowering traditional industries with new technologies, creating new industries, and fostering innovative models within these industries [1–4]. The DGE has become a crucial driver for driving national economic growth [5,6].

The report of the 20th National Congress of the CPC emphasized that "accelerating DGE development strengthens the foundation for CMP by promoting the deep integration of the DGE with the real economy". Temporally, the rapid development of China's DGE aligns with the era of CMP, indicating that achieving CMP relies on the development of DGE [7–9]. From a goal-driven perspective, the DGE can promote equitable income distribution through spillover effects, synergies, and inclusive effects, thereby facilitating CMP realization [10–14].

Firstly, the DGE could improve the matching efficiency between supply and demand [15], bringing production closer to the possibility frontier at the macro level and pushing the frontier outward. This serves as an important guarantee for the accumulation of material wealth necessary to achieve CMP [16,17]. The China DGE Development Research Report (2024) states that in 2023, the scale of China's DGE hit 53.9 trillion yuan, representing 42.8% of GDP. This contribution is similar to that of the secondary industry to the national economy. Secondly, the development of the DGE exerted a positive influence on public services [18], regional disparities [19,20], employment [21–24], and entrepreneurship [25,26]. It was found to be closely linked to numerous areas, including distributional equity [27,28], wealth accumulation [29,30], and welfare improvement [31,32]. It also played a crucial role in determining whether the benefits of reform and development could be extended to the broader population. The DGE is referred to as the key to unlocking the Fourth Industrial Revolution. With its inherent technological characteristics of network distribution and decentralization, it is poised to break the traditional spatial organization of economic factors. Therefore, exploring how the DGE can achieve CMP should be based on spatial models, investigating whether and how the development of DGE empowers CMP, as well as the variations in its effects.

The Yellow River Basin (YRB) is not only an important economic belt traversing the eastern, central, and western regions. It is also a major ecological barrier economic zone in China [33], making it a key area for achieving CMP [34]. The Yellow River Protection Law of the People's Republic of China officially came into force on 1 April 2023. This law, aimed at balancing between ecological sustainability and economic prosperity, offers strong support for advancing CMP in the YRB. However, constrained by factors such as natural and historical conditions, the realization of CMP in the YRB still faces numerous challenges, such as a fragile ecological environment [35,36], weak technological innovation capabilities [37], and a low level of green development [38]. As the main driving force for advancing CMP in China, the DGE uses information technology to promote balanced and coordinated economic and social development. It brings historic opportunities to expand new development space and cultivate new development advantages [39] along the YRB.

Therefore, this study takes spatial economics as the starting point to examine whether the DGE is influenced by factors such as location conditions, public service levels, and industrial structure differences, as well as how these factors produce varying spatial effects on CMP development. This provides theoretical support for achieving CMP sooner. The potential innovations are the following: (1) It explores the spatial nonlinear effects of the DGE's empowerment of CMP, conducts an exploratory spatial analysis of empowerment factors in conjunction with synergy theory and endogenous growth theory, and supplements existing research; (2) it aligns the concept of "Big Data (BD)" construction with the digital empowerment of urban development, introduces the BD pilot policy as an exogenous shock, and separates spillover effects between the treatment group and the control group, effectively validating the spatial impact of DGE; and finally, (3) it focuses on the boundaries of spatial spillover effects and spatial heterogeneity, enriching the study of the spatial effects of DGE on CMP.

The remainder of this study is structured as follows: Section 2 summarizes the relevant literature and analyzes the mechanisms through which DGE enables CMP. Section 3 constructs the DGE and CMP index systems and introduces the SDM, SPSTR, and SDID models, along with the mechanism variables and data sources. In Section 4, the spatial evolution patterns of the DGE and CMP are visually analyzed. In Section 5, the DGE spillover effect is analyzed using the SDM model, robustness and endogeneity tests are conducted, and the spatial spillover effect of the DGE on CMP is further verified using the SDID model. In Section 6, the overflow boundaries and heterogeneity of DGE-enabled

CMP are analyzed. In Section 7, the nonlinear relationship between industrial structure evolution and Basic Public Service regarding DGE-enabled CMP is analyzed using the SPSTR model. Section 8 summarizes the conclusions and policy implications. Section 9 discusses the limitations.

2. Literature Review and Research Hypotheses

2.1. Literature Review

2.1.1. DGE and Economic Growth

Existing research has widely recognized that the DGE, as an emerging social form, drove economic growth by optimizing the allocation of traditional production factors and enhancing economic innovation vitality [1,4]. It not only created new economic growth drivers but also provided technical support and innovative pathways for achieving sustainable development [21].

At the macro level, the DGE leveraged data elements to enhance resource allocation efficiency through intelligent and information-based methods, which led to reductions in energy consumption and carbon emissions, ultimately achieving long-term economic growth and facilitating green transformation [7,13,40,41].

At the meso level, digital technologies facilitated the digital transformation and green upgrading of traditional industries through industrial innovation, correlation, and integration effects [24,42]. For instance, research conducted by Zhang and Qian found that green finance initiatives significantly enhanced resource utilization efficiency in energy-intensive industries, reduced pollutant emissions, and supported the optimization of industrial structures, thereby contributing to green development goals [11,43].

At the micro level, enterprises reshaped their mechanisms for capturing innovation value through the integration of information technologies [44]. This integration improved production efficiency and technological innovation [45] while reducing environmental impacts through the adoption of intelligent management systems and green supply chains [46], thereby promoting sustainable development.

2.1.2. DGE and Public Services

Research showed that the proliferation of digital technologies helped narrow the gaps between urban and rural areas, as well as among different regions, thereby facilitating the sharing of public services [20,47,48]. The application of digital technologies not only reduced public service costs but also improved the efficiency of resource allocation, particularly in critical areas such as healthcare [18], education [49], and social security [47], where information technology enhanced both the accessibility and quality of services.

The development of digital platforms further expanded public service coverage. By employing big data analytics and artificial intelligence technologies [50], the transparency and effectiveness of public resource allocation improved [51], addressing issues such as uneven resource distribution and service quality disparities. Additionally, digital technologies drove innovations in government management models [31,52], enabling the intelligent and precise delivery of public services. These advancements better addressed diverse social needs, improved social welfare [53], and enhanced public service quality [54], thus promoting the modernization of the public service system.

2.1.3. DGE and CMP

Research on the relationship between the DGE and CMP witnessed various scholars conducting analyses from different perspectives. Some scholars focused on the connotations and measurements of the DGE [16,17], its role in optimizing and upgrading industrial structures, and its impact on narrowing the urban–rural gap [14,20,23,55]. Other scholars emphasized factors influencing high-quality economic development in specific regions, analyzing mechanisms that drove high-quality economic development among cities [5,7,19,56] within and between regions from the perspectives of technological innovation [37], industrial structure [24], and increased marketization.

Additionally, some researchers investigated the spatial spillover effects of the DGE [10,57], which enhanced technological innovation in industries and promoted the upgrading of traditional industrial structures [34,58,59]. This, in turn, facilitated high-quality development and contributed to the CMP of neighboring regions. Zhou and Guo's research [60], which is related to the theme of this study, explored the impact of the regional DGE on CMP; however, they did not consider the spatial spillover effects of digitalization.

Currently, valuable research has been accumulated regarding both the DGE and CMP, but several shortcomings remained: First, much of the literature on CMP has been qualitative in nature. Second, there is still no research that has investigated the impact of the DGE on CMP from the perspective of regional spatial economics. Third, the existing literature does not adequately address the digital spillover effects of the DGE at the regional and urban levels.

In light of the above shortcomings, the improvements made in this study are as follows: First, this study built upon existing studies by utilizing a threshold method to measure CMP levels at the city level in the YRB, focusing on both the monitoring of the CMP process and outcome orientation. Historical data were employed to create instrumental variables to mitigate the potential endogeneity of the DGE. Second, the BD policy was introduced as an empirical validation of exogenous shocks. The SDID model was utilized to assess its impact on the empowerment of CMP by the DGE, enhancing the robustness of this study. Third, unlike previous studies that relied on linear models, this study combined the spatial nonlinear SPSTR model to more accurately capture the dynamic spillover process of DGE enhanced CMP.

2.2. Research Hypotheses

Currently, China faces challenges in the development of CMP, such as an imperfect income distribution system, uneven public service provision, and disparities in employment quality [61]. As a key force in the transition between old and new economic drivers, the DGE, characterized by strong penetration, cross-temporal and spatial reach, and a shared nature, can effectively overcome the critical barriers to both "making a bigger cake" and "dividing a better cake" equitably. This creates favorable conditions for promoting a comprehensive, inclusive, and co-constructed prosperous society [8,9,47].

2.2.1. The DGE's Empowerment of CMP Exhibits Spatial Spillover Effects

Digital infrastructure construction is based on communication networks, with computing power networks at the core that are driven by data innovation. They have exhibited strong "penetration effects" that create conditions for technology diffusion and knowledge generation [62,63]. The cross-border integration and instant sharing characteristics of digital technology break the information isolation and monopoly barriers of the traditional economy. In terms of algorithms and computing efficiency, they demonstrate spatial–temporal universality and high connectivity, serving as a driving force for achieving regional coordinated development and inclusive growth [44,64]. Data elements possess characteristics such as nonscarcity and nonexclusivity, enabling a better balance of efficiency and equity when involved in distribution [51]. This brings new opportunities for achieving CMP.

The DGE has promoted a more decentralized regional industrial layout, enhancing the balance and coordination of regional development [58]. The impact of geographical distance on industrial agglomeration, the regional division of labor, and transaction efficiency diminished [65], further strengthening the dynamic interaction, spatio-temporal compression, and multidimensional heterogeneity of new regional economic networks. As digital technology iterates and application scenarios expand, the spatial organization of production factors such as talent, knowledge, and technology gradually transforms into a fluid space [42], expanding the domain of regional development [66].

At the same time, various factors broke traditional hierarchical systems, relying less on geographical location radiation, with an increase in leapfrogging diffusion [67]. This resulted in new spatial–temporal location dominance patterns, leading to the deconstruction or reconstruction of multicentered economic spaces [68]. A key tool for regional spatial governance in developed countries has been the integration of regional economic spaces with DGE layouts, building a multidimensional spatial network that has facilitated the flow of production factors, reshaping government organizational methods, and providing momentum for the construction of CMP demonstration zones [69].

Additionally, the development of the DGE in China at the provincial level has generally exhibited a stepped distribution pattern, with significant spatial heterogeneity [70]. The YRB spans a wide geographical area, with considerable differences in ecological resource endowments and regional development foundations [33]. The uneven and insufficient socio-economic development along the basin [35], particularly the significant disparities in DGE development levels between the upper, middle, and lower reaches, has led to varying effects on empowering CMP. Accordingly, these research hypotheses were proposed:

Hypothesis 1: *The DGE, as an endogenous driver, has spatial spillover effects in empowering CMP.*

Hypothesis 1a: *The integration of the DGE with regional economic spaces breaks down administrative boundaries, overcomes spatial limitations, and empowers the realization of CMP.*

Hypothesis 1b: *The impact of the DGE in empowering CMP exhibits spatial heterogeneity.*

2.2.2. The DGE Empowers CMP with a Nonlinear "Making a Bigger Cake" Effect

Data elements refer to data resources that exist in electronic form and contribute significant value to production and business activities through computational processes. These data elements exhibit positive externalities [71], coordinating the optimization and reorganization of traditional production factors such as technology, labor, and capital while driving technological transformation. They have reshaped production relations and the synergy among factors, leading to the diversification of industry types, breaking information silos, and fostering industrial linkages. The diffusion of information technology reduced transaction costs [40], improved production and management efficiency [72], accelerated industrial transformation, enabled green production [43,59], and promoted the evolution of industrial structures, making a bigger and better cake for achieving CMP.

Digital platforms have served as central hubs for integrating technology, aggregating data, and empowering digital services. They gave rise to new consumption models, expanded service offerings, and drove the growth of the tertiary sector from the demand side. The emerging consumer needs prompted companies to pursue high-tech innovations, facilitating the transition of the industrial structure toward advanced levels. Through digital platforms, DGE-enabled data interactions across networks, enterprises, and regions allowed for the scientific and effective implementation of credit evaluation, customer segmentation, and risk management. This facilitated the accurate matching of consumers with producers, yielding smart dividends and improving resource efficiency [15,18,34,41]. The "long tail effect" was fully utilized, exerting a nonlinear positive impact on total factor productivity [73]. It helped reduce information asymmetry, lower intermediary costs, enhance resource utilization and energy output rates, and promoted the rational evolution of the industrial structure, empowering CMP.

The integration of the DGE with the real economy reshaped market demand and restructured the industrial chain, leading to the redistribution of the market division system and industrial value chain. The digital economy's driving force and positive impact on new industrial transformations prompted the real economy to undergo digital, green, networked, and intelligent transitions [59]. This reshaped industrial structures and forms, accelerated the shift from old to new growth drivers, and became a new pillar for advancing CMP. Accordingly, the following research hypothesis was proposed:

Hypothesis 2: *The DGE has significant amplification and compounding effects, with Industrial Structure Evolution empowering CMP through marginally increasing returns, thereby enhancing the "making a bigger cake" effect of overall prosperity.*

2.2.3. The DGE Empowers CMP with an Inclusive Growth "Dividing a Better Cake" Effect

The DGE, through a dual empowerment model of "external momentum supply + internal potential" has narrowed development gaps across various dimensions, promoted the coordinated regional development and equalization of public services, and ensured that all people shared in the benefits of reform and development.

Firstly, the DGE accelerated the spillover of public services and the sharing of resource flows, empowering the balanced allocation of regional public service resources and dividing a better cake for achieving CMP. Thus, the following outcomes have taken place: (1) Digital sharing platforms improved public service equalization by enhancing supply–demand matching accuracy, reducing transaction costs, and expanding service boundaries [51]. (2) Deep learning algorithms integrated the vast information and decentralized resources provided by big data, breaking temporal and spatial limitations [74] and accurately identifying the effective needs for essential public services, such as healthcare, basic education, cultural and sports activities, and public housing among key groups, including disadvantaged individuals, migrant workers, and left-behind families. (3) The application of digital technology facilitated cooperation among service providers across different regions. By leveraging the shared nature of data elements [75], the traditional fragmentation of public services was overcome, enhancing resource allocation and flexible scheduling. This promoted the coordination and sharing of public services among urban clusters, bridging service gaps in underdeveloped areas.

Secondly, internal potential has been leveraged to achieve inclusivity effects and share the digital dividends. (1) The application of digital technology to government management and services enhanced the government's regulatory strength and effectiveness in public service areas such as transfer payments, administrative services, and social assistance [31,52]. (2) A digital scenario-based comprehensive regulatory mechanism and feedback process has been established to strengthen the quality and quantity of public service provision. It promoted the equalization of basic public services and ensured fairness in secondary distribution [51]. (3) As digital infrastructure became widely integrated into production and daily life, it provided more learning opportunities for vulnerable groups such as the elderly, the unemployed, and migrant workers, bridging the digital usage divide, enhancing workers' skills and capabilities [14,21], and expanding employment choices and support avenues for low-skilled workers. It also fostered an interactive collaboration system among government, charitable organizations, and businesses; perfected the charitable ecosystem; and fully utilized the supplementary role of tertiary distribution in promoting fairness. Accordingly, the following research hypothesis was proposed:

Hypothesis 3: *The DGE has distinct spillover and inclusive effects, with the equalization of Basic Public Services serving as an endogenous driver for empowering CMP, thereby enhancing the "dividing a better cake" effect of shared prosperity.*

This study framework is showed in Figure 1:

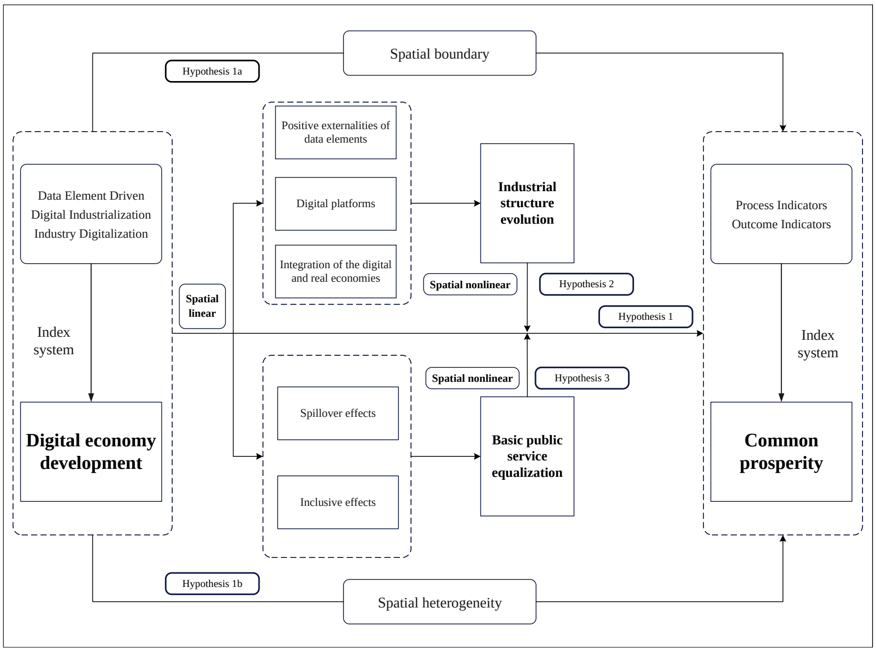

Figure 1. Flow chart.

3. Methodology

3.1. Indicator Construction

3.1.1. CMP Index System

CMP is regarded as the organic unity of "commonality" and "prosperity", where "commonality" reflects the systematic manifestation of production relations across various fields, and "prosperity" represents the overall level of social productivity [8]. The concepts of "commonality" and "prosperity" encompass all aspects of "economic, political, cultural, social, and ecological development" [9]. Economic development serves as the foundation, income growth as the main focus, and shared outcomes as the guiding principle. The construction of its indicator system emphasizes the following: (1) The two key elements, "commonality" and "prosperity", are targeted to address various factors and disparities affecting common prosperity [48]. (2) CMP is viewed as a process evolving from lower to higher levels, from local to comprehensive, and from initial prosperity to widespread prosperity [76]; thus, the evaluation indicator system needs to capture this dynamic process. (3) Efforts are aimed at narrowing disparities without promoting egalitarianism. With reference to relevant research experience, this study aims to establish a CMP evaluation system that integrates both process and outcome indicators. The entropy-weighted TOPSIS method calculates the indicator weights—denoted as CMP. The detailed index is presented in Table 1. The calculation of indicators and data sources is detailed in Appendix A and Table A1. The indicators are explained below in Appendix A; see Table A1.

Table 1. Index system of CMP.

Level 1	Level 2	Level 3	Attributes	Weight
Process Indicators	Efficiency Improvement	Per capita GDP	+	0.0714
		Labor productivity	+	0.0632
	Innovation Driven	R&D/GDP	+	0.0284
		Invention patents/10,000 individuals	+	0.0306
	Structural Optimization	Engel coefficient	–	0.0137
		Contribution rate of household consumption	+	0.0119

Table 1. *Cont.*

Level 1	Level 2	Level 3	Attributes	Weight
Process Indicators	Income Security	Per capita disposable income	+	0.0430
		Labor compensation/GDP	+	0.0347
	Energy Conservation	Treatment rate of sewage treatment plants	+	0.0058
		Carbon emissions/GDP	–	0.0107
		Energy consumption/GDP	–	0.0112
	Ecological Quality	$PM_{2.5}$ concentration	–	0.0248
		Per capita green space area	+	0.0549
		Greening coverage rate	+	0.0189
		Air quality index	+	0.0224
	Cultural Literacy	Per capita library collection	+	0.0379
		Employees in the cultural industry total amount	+	0.0379
	Quality of Life	Total hospital beds and doctors/10,000 individuals	+	0.0548
		Intensity of education expenditure	+	0.0699
		Road mileage/10,000 individuals	+	0.0239
		Public transport vehicles/10,000 individuals	+	0.0371
		Per capita housing area	+	0.0087
		Housing price/per capita disposable income	–	0.0050
Outcome Indicators	Population Differences	Average wage disparity across industries	–	0.0144
		Healthcare coverage disparity across industries	0	0.0088
	Urban–Rural Differences	Urban–rural development disparity coefficient	0	0.0235
		Urban–rural education gap	–	0.0176
		Urban–rural employment burden ratio	–	0.0185
		Urbanization rate	+	0.0532
	Income Differences	Income disparity coefficient	0	0.0526
		Prosperity intensity index	+	0.0272
	Regional Differences	Regional development disparity coefficient	0	0.0291
		Disparity in basic public services across regions	–	0.0176

Note: According to the indicator attributes, all indicators are classified into three categories: positive (+), negative (−), and moderate (0).

3.1.2. DGE Index System

The DGE evaluation system was constructed based on macro-level policy documents directly related to the DGE such as the "14th Five-Year Plan for DGE Development" and the "2021 Statistical Classification of the DGE and Its Core Industries". The indicator system for digital development formulated by the China Academy of Information and Communications Technology and other relevant studies [16,77] were also consulted. Consideration was given to the actual conditions and regional disparities in digital economic development, while the availability of different data indicators was comprehensively assessed. The principles of scientific validity, systematicity, comparability, and feasibility were followed in the construction process. A DGE evaluation index system was constructed (Table 2). The entropy-weighted TOPSIS method was used for weight allocation, resulting in the DGE index. The calculation of indicators and data sources is detailed in Appendix A; see Table A2. The indicators are explained below in Appendix A; see Table A2.

Table 2. Index system of DGE.

Level 1	Level 2	Level 3	Attributes	Weight
Digital Element Driven	Digital Infrastructure	Internet broadband access ports/Population	+	0.0720
		Mobile phone users/100 individuals	+	0.0840
		Mobile phone base station total amount	+	0.0709
	Digital-Driven Production	IPV4/IPV6	+	0.0804
		Big data centers	+	0.0591
Digital Industrialization	Industry Scale	Revenue from telecommunications and postal services	+	0.0657
		Employees in information and software services total amount	+	0.0842
	Industry Category	Number of listed companies in intelligent manufacturing	+	0.1006
		Listed ICT companies total amount	+	0.0646
Industrial Digitization	Service Industry Digitization	E-Government service platforms	+	0.0486
		E-Commerce transaction volume	+	0.0326
	Industrial Digitization	Industrial internet patents granted's number	+	0.1133
		Penetration rate of digital high-tech applications	+	0.0687
		Density of industrial robot installations	+	0.0553

Note: According to the indicator attributes, all indicators are positive (+).

3.1.3. Mechanism Variables

(1) "Making a Bigger Cake"—Industrial Structure Evolution (ISE): The DGE positively influenced industrial structure upgrading through the industrial internet and capital deepening, increasing the productivity of "stagnant sectors" while expanding the proportion of "progressive sectors". This drove the rationalization of industrial structures, promoting coordinated development across industries, sectors, and regions. Therefore, this study used industrial structure rationalization to represent industrial structure evolution.

$$ISE_{i,t} = \sum_{n=1}^{3} X_{i,n,t} \times \ln(X_{i,n,t}/z_{i,n,t}) \tag{1}$$

where n = 1, 2, 3 denote the primary, secondary, and tertiary industries[1]. The variable $z_{i,n,t}$ represents the proportion of employees in the nth industry relative to the total number of employees in city i during period t.

(2) "Dividing a Better Cake"—Basic Public Service Equalization (BPS): The impact of the DGE on CMP is, to some extent, mediated by the BPS. Following relevant research [53,54], this study represents BPS using two indicators: demand and supply. The demand indicators include the minimum number of insured persons and the ratio of unemployed individuals to those receiving retraining. The supply indicators include social security coverage and the population receiving compulsory education. The level of BPS in cities along the YRB was measured using the entropy-weighted TOPSIS method.

3.1.4. Control Variables

The impact of the DGE on CMP is influenced by various factors, including regional differences, industrial structure, and education [9,34,76]. The control variables selected in this study are as follows:

Industrial Structure Upgrading (IS): The formula is

$$IS_{i,t} = \sum_{n=1}^{3} g_{i,n,t} \times LP_{i,n,t}, \quad n = 1,2,3 \tag{2}$$

where $LP_{i,n,t} = AV_{i,n,t}/E_{i,n,t}$ represents the labor productivity of the primary, secondary, and tertiary industries in city i during period t. $AV_{i,n,t}$ represents the added value of the nth industry in city i during period t compared to period $t-1$. $E_{i,m,t}$ represents the number of employees in the nth industry in city i during period t, and $g_{i,n,t}$ represents the proportion of the nth industry of the total GDP of city i during period t.

Degree of Openness (OP): This defines total foreign trade (imports and exports)/GDP.

Environmental Regulation (ER): This is represented by the frequency of environment-related terms appearing in city government work reports.

Financial Development (FD): This defines the balance of loans from financial institutions at year-end/GDP.

Education Level (ED): This is represented by the average years of education per capita.

Social Welfare Level (SW): This is represented by the logarithm of the number of beds in social welfare institutions.

Government Intervention (GI): The defines fiscal expenditure/GDP.

3.2. Data Sources

The relevant data were primarily sourced from the China Urban DGE Development Report, the Digital China Index Report, the China City Statistical Yearbooks, Provincial Statistical Yearbooks, the China E-Government Development Report, various city statistical bulletins, the International Federation of Robotics, the websites of various cities' Bureaus of Industry, Information Technology, Statistics, the CSMAR database, and the Wind database. Some data also came from the research group's surveys. This study selected 76 prefecture-level cities in the YRB as the study area[2], with 2011–2021 as the study period. The sample was processed as follows: (1) A mixed-frequency dynamic factor algorithm was used to supplement a small amount of missing data. (2) To eliminate the effects of different dimensions and ensure the comparability of the same indicators across different years, this study used 2011 as the base year and applied the threshold method to standardize the tertiary indicators of CMP and DGE.

3.3. Model Construction

3.3.1. Spatial Durbin Model

The DGE variables examined in this study exhibited strong spatial externalities, making it necessary to incorporate spatial effects when exploring the relationship between DGE and CMP. Based on the works of Anselin [78] and Elhorst [79], the following spatial model was first established:

$$CMP_t = \delta WCMP_t + \alpha\iota_N + DGE_t\beta_1 + WDGE_t\theta_1 + K_t\beta_2 + WK_t\theta_2 + \mu + \zeta_t\iota_N + \mu_t \quad (3)$$

Here, $t = 1, 2, \cdots, T$ represent the years, CMP denotes the common prosperity index, DGE is the digital economy index, and K represents control variables. ι_N is an $N \times 1$ unit vector, $\alpha\iota_N$ represents individual fixed effects, and $\zeta_t\iota_N$ represents time fixed effects. W is the spatial weight matrix, and μ_t is the random error term.

3.3.2. SPSTR Model

Equation (3) shows the linear form of the spatial impact model of DGE on CMP. However, the CMP driven by the DGE involves multiple conditional constraints. Therefore, this study further considered spatial nonlinear models. The Panel Threshold Regression (PTR) model proposed by Hansen [80] and the Spatial–Temporal Autoregressive (STAR) model proposed by Teräsvirta [81] provided important theoretical foundations for establishing nonlinear regression models. PTR regression coefficients can describe the transition of variables from one regime to another; however, this change was discontinuous and did not align with the real patterns of economic and social development. To address this issue, González et al. [82], building on the PTR and STAR models, established a transition function with exogenous explanatory variables and created the Panel Smooth Transition Regression (PSTR) model [83], which generally takes the following form:

$$y_{it} = \mu_i + \beta_0' x_{it} + \beta_1' x_{it} g(q_{it}; \gamma, c) + \varepsilon_{it} \tag{4}$$

Here, $i = 1, \cdots, N$, $t = 1, \cdots, T$, and μ_i represent individual fixed effects. β_0 and β_1 represent the linear and nonlinear parts of the estimated parameters, respectively, and ε_{it} is the random error term. Given that $g(q_{it}; \gamma, c)$ is a continuous and bounded function that needs to converge between 0 and 1, it is more reasonable to use a logistic transition function to describe the transition of variables between different regimes. The specific expression is as follows:

$$g(q_{it}; \gamma, c) = \left\{ 1 + \exp\left[-\gamma \prod_{j=1}^{m} (q_{it} - c_j) \right] \right\}^{-1}, \gamma > 0, c_1 \leq c_2 \leq \cdots \leq c_m \tag{5}$$

In Equation (5), q_{it} is the transition variable; γ is the smooth transition coefficient; and $c = (c_1, \cdots c_m)'$ represents an m-dimensional vector of location parameters. Model identification is achieved by imposing the constraints $c = c_1 \leq c_2 \leq \cdots \leq c_m$ and $\gamma > 0$. Taking m=1 as an example, the PSTR model implicitly contains two extreme regimes, with the coefficients of the explanatory variable x_{it} transitioning from β_0 to $\beta_0 + \beta_1$ as the transition variable q_{it} changes around the location parameter c.

Building on Equations (3)–(5), this study incorporated spatial lag variables into the model, extending the PSTR model to the Spatial Panel Smooth Transition Model (SPSTR). The SPSTR can capture the smooth transition process of the transition variable across different economic states, providing a more precise explanation of the dynamic spatial spillover effects of the DGE on CMP. The specific expression is as follows:

$$\begin{aligned} CMP_t = \delta WCMP_t + \alpha \iota_N + DGE_t \beta_1 + WDGE_t \theta_1 + K_t \beta_2 + WK_t \theta_2 + \zeta_t \iota_N + \\ (\delta WCMP_t + \alpha \iota_N + DGE_t \beta_1 + WDGE_t \theta_1 + K_t \beta_2 + WK_t \theta_2) \times G(q_{it}; \gamma, c) + \mu_t \end{aligned} \tag{6}$$

3.3.3. Spatial DID Model

The DID method is a principal approach for evaluating policy effects, as it controls for pre-existing differences among study subjects and effectively addresses endogeneity issues. This study used the construction of "Big Data (BD)"[3]. This construction was used as an exogenous policy shock to assess the impact of DGE on CMP. This study constructed a Spatial DID (SDID) model based on the SDM.

$$\begin{aligned} CMP_{it} = \gamma + \alpha_i \iota_N + \delta_1 WCMP_{it} + \beta_1 BD_{it} + \delta_2 WBD_{it} + \beta_2 K_{it} + \delta_3 WK_{it} \\ + \delta_4 (W_{T,T} + W_{T,NT} + W_{NT,T} + W_{NT,NT}) BD_{it} + \zeta_t \iota_N + \varepsilon_{it} \end{aligned} \tag{7}$$

Here, BD indicates whether city i in year t is a "Big Data" pilot (with a value of 1 for pilot cities and 0 otherwise); γ, δ, β are the parameters to be estimated. T represents the treatment group, and NT represents the control group. $W_{T,T}$ BD_{it} represents the indirect effects of the treatment group on the treatment group, while $W_{NT,T}$ BD_{it} represents the indirect effects of the treatment group on the control group. Clearly, $W_{T,NT} = 0$, and $W_{NT,NT} = 0$. The final form of Equation (7) is written as follows:

$$\begin{aligned} CMP_{it} = \gamma + \alpha_i \iota_N + \delta_1 WCMP_{it} + \beta_1 BD_{it} + \delta_2 WBD_{it} + \beta_2 K_{it} \\ + \delta_3 WK_{it} + \delta_4 (W_{T,T} + W_{NT,T}) BD_{it} + \zeta_t \iota_N + \varepsilon_{it} \end{aligned} \tag{8}$$

3.3.4. Spatial Weight Matrix

This study drew on the method proposed by Thompson et al. [84] and constructed a spatial weight matrix based on a gravity model that combined economic links and geographic distance[4].

$$W_{ij} = \begin{cases} \frac{GDP_i \times GDP_j}{d_{ij}^2}, & i \neq j; \\ 0, & i = j \end{cases} \tag{9}$$

To analyze the impact of DGE on CMP within different spatial threshold ranges, a spatial weight matrix was constructed with a critical value every 50 km within the 0–1500 km range. This approach was used to examine the spatial boundaries of the spillover effects of DGE on CMP.

4. Spatial Evolution Patterns of DGE and CMP

4.1. Spatial Distribution Characteristics of DGE in Cities Along the YRB

This study used the natural breaks method to classify the types of DGE levels. DGE levels were classified as lagging, improving, pioneering, or leading regions and visualized using ArcGIS 10.8 software, as depicted in Figure 2. From a spatial perspective, the DGE level in most cities has significantly improved between 2011 and 2021, with the most notable enhancements occurring from 2015 to 2021. Since 2011, cities such as Xi'an, Jinan, and Taiyuan have experienced rapid DGE development, whereas cities like Chifeng, Pingliang, and Tongliao have seen relatively slower progress. It is worth noting that in 2015, Nanyang's DGE level was in the higher improvement and pioneering stages compared to surrounding cities. However, by 2021, Nanyang and its neighboring cities had reached the same pioneering stage in DGE development.

By 2021, the spatial pattern of the DGE in cities along the YRB exhibited a "downstream high, upstream low" characteristic. Downstream areas cities generally had higher levels of DGE development compared to upstream areas. This pattern was primarily centered around Qingdao, Jinan, and Zhengzhou, with the DGE development level gradually decreasing toward the midstream and upstream areas. Xi'an and Zhengzhou emerged as secondary cores of high DGE development within the YRB.

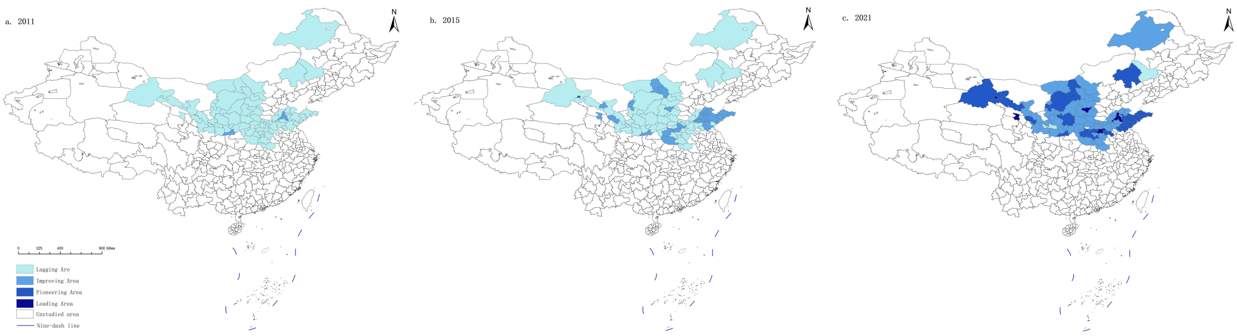

Figure 2. Spatial evolution pattern of DGE in the YRB. Note: Figures 2 and 3 are based on the standard map of the Map Technical Review Center of the Ministry of Natural Resources (No. GS(2022)4309), and the base map is not modified.

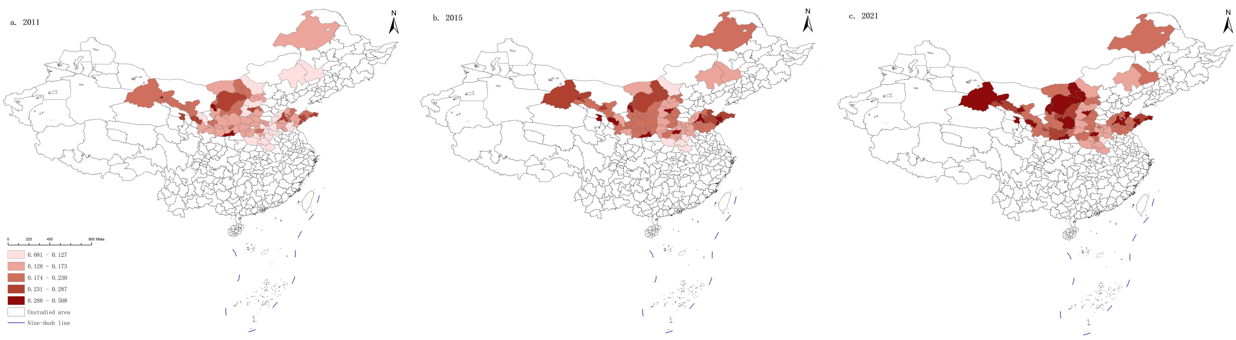

Figure 3. Spatial evolution pattern of CMP in the YRB.

4.2. Spatial Distribution Characteristics of CMP in Cities Along the YRB

This study divided the CMP index into five levels to explore the evolutionary characteristics of the spatial distribution of CMP in cities along the YRB, as detailed in Figure 3.

Overall, the pattern of CMP levels in the YRB shifted from a scattered pattern with multiple centers scattered distribution centered around provincial capitals to a "clustered" aggregation form. By 2021, the level of CMP in areas surrounding core cities had significantly improved, with notable differences in CMP development across the downstream, midstream, and upstream areas. The range of CMP index changed from 0.081–0.303 in 2011 to 0.126–0.487, with the numerical gap widening, indicating a clear trend of regional development divergence and persisting issues of imbalance and inadequacy in development.

This may be due to the insufficiently high-quality development of cities along the YRB. The regions are predominantly characterized by agriculture, animal husbandry, energy, chemical industries, and raw materials, with significant reliance on energy and heavy industries. Additionally, due to geographical constraints, the economic connectivity among cities along the YRB is relatively weak, and the mechanism for coordinated development is not yet fully developed. The awareness of regional division of labor and collaboration urgently needs to be strengthened.

4.3. Spatial Correlation

Before estimating Equation (3), the spatial correlation between the DGE and CMP in the YRB cities should be tested. Appendix A through Table A3 shows that the Moran's I index *p*-values for both the DGE and CMP in the YRB from 2011 to 2021 were all less than 0.01, significantly positive at the 1% level, and exhibited an increasing trend. This indicates a clear spatial dependence between the DGE and CMP. The spatial pattern evolution characteristics shown in Figures 2 and 3 further confirm the clustering effect of the DGE and CMP.

5. The Spatial Impact Effect of DGE on CMP

5.1. Overall Impact Effect

This study conducted LR, LM, Hausman, and Wald tests, all of which passed the 1% significance level. Additionally, the optimal model among the SLM, SEM, and SDM was selected based on a combination of the natural logarithm of the likelihood function, goodness-of-fit, and other statistics (see Appendix A in Table A4) [85]. By combining these evaluation methods, it was determined that the SDM with two-way fixed effects was the best estimation model. The results of the estimation are shown in Table 3.

Table 3. Regression results.

Variables	(1) SLM	(2) SEM	(3) SDM	(4) SDM-W1	(5) SDM-X1	(6) DSDM	(7) IV-W
DGE	0.056 ***	0.066 ***	0.055 ***	0.053 ***	0.023 **	0.032 ***	0.086 ***
	(2.87)	(3.18)	(2.66)	(2.66)	(2.49)	(2.82)	(2.52)
ISE	0.044 *	−0.011	−0.004	−0.027	0.037	0.030	0.139 ***
	(1.81)	(−0.37)	(−0.13)	(−0.93)	(1.41)	(1.07)	(12.03)
IS	−0.003	0.001	−0.001	−0.001	−0.010 ***	−0.011	−0.120 ***
	(−0.63)	(0.26)	(−0.16)	(−0.17)	(−2.68)	(−0.62)	(2.88)–
OP	0.009	0.008	0.007	0.007	0.010 *	0.011 *	0.105 ***
	(1.53)	(1.34)	(1.17)	(1.14)	(1.89)	(1.90)	(9.91)
ER	0.001 *	0.001 *	0.001 **	0.001 ***	0.001 **	0.001 **	0.001 **
	(1.87)	(1.71)	(2.45)	(2.74)	(2.36)	(2.41)	(2.16)
FD	0.001	0.001	0.001	0.000	−0.000	−0.000	0.036
	(1.26)	(1.12)	(1.04)	(0.96)	(−0.31)	(−0.47)	(0.63)
ED	0.001 ***	0.001 ***	0.001 ***	0.001 ***	−0.001 ***	−0.001 **	−0.05 ***
	(3.59)	(3.29)	(3.36)	(2.77)	(−4.20)	(−2.20)	(−6.50)
SW	−0.051	−0.055	−0.073	−0.037	0.003 ***	0.003	0.001
	(−0.78)	(−0.83)	(−1.10)	(−0.58)	(12.53)	(1.59)	(0.58)
GI	0.001	0.001	0.001	0.000	0.003	0.008	−0.001
	(0.79)	(0.48)	(0.97)	(1.19)	(0.05)	(0.14)	(−0.16)

Table 3. *Cont.*

Variables	(1) SLM	(2) SEM	(3) SDM	(4) SDM-W1	(5) SDM-X1	(6) DSDM	(7) IV-W
ρ	0.722 ***		0.551 ***	0.562 ***	0.684 ***	0.448 ***	0.510 ***
	(22.19)		(11.09)	(7.06)	(9.58)	(6.78)	(6.06)
ψ		0.823 ***					
		(38.80)					
W×DGE			0.302 ***	0.204 ***	0.026 **	0.150 ***	0.265 ***
			(5.37)	(3.39)	(2.09)	(2.88)	(10.08)
W×ISE			0.100	0.062	−0.105	−0.072	−0.066 ***
			(1.57)	(0.51)	(−0.90)	(−1.16)	(−7.17)
W×IS			0.022	0.057 *	0.087 ***	0.022	−0.039 *
			(1.51)	(1.72)	(3.08)	(1.55)	(−2.36)
W×OP			−0.001	−0.069	−0.067 *	−0.033	0.026 ***
			(−0.05)	(−1.57)	(−1.76)	(−1.64)	(12.56)
W×ER			0.001	0.002	0.002	0.001	0.002 ***
			(0.76)	(0.76)	(0.82)	(1.51)	(4.48)
W×FD			−0.003	−0.007 *	−0.006 *	−0.000	0.004 **
			(−1.53)	(−1.92)	(−1.71)	(−0.18)	(3.08)
W×ED			−0.001	−0.008 ***	−0.001	0.003 ***	0.004 **
			(−0.65)	(−3.44)	(−0.39)	(3.05)	(2.90)
W×SW			0.144	0.626	−0.008 ***	−0.004 ***	0.001
			(0.61)	(1.24)	(−6.09)	(−6.66)	(0.32)
W×GI			0.001 **	0.004 ***	0.936 **	0.245	0.199 ***
			(2.13)	(2.63)	(2.06)	(1.16)	(4.28)
L.W×CMP						0.584 ***	
						(6.39)	
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	836	836	836	836	836	760	836
R^2	0.229	0.264	0.305	0.248	0.286	0.269	0.237

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, with values in parentheses representing z-test .

In the SLM, SEM, and SDM models, both ρ and ψ were significantly positive at the 1% level, indicating a clear spatial dependence in the DGE's empowerment of CMP. The DGE's development can promote technological progress and knowledge diffusion while overcoming resource constraints and spatio-temporal limitations. Data elements, characterized by low replication costs and noncompetitiveness, provided an inclusive mechanism for balanced and coordinated development, accelerating the achievement of CMP.

5.1.1. Robustness Test

To avoid potential biases in the results due to measurement errors, endogeneity, and other issues, as well as to ensure the reliability of research conclusions, robustness tests were conducted as follows:

(1) Transformation of Spatial Weight Matrix: Considering that DGE development was found to be highly dependent on network information development levels, this study constructed the weight matrix by the product of information development levels between cities and the reciprocal of their centroid distances[5]. The results in Table 3 column (4) compared to (3) show that the impact of the DGE on CMP development only exhibited a change in the magnitude of coefficient, indicating the chosen weight matrix's strong applicability and robustness.

(2) Replacement of Core Explanatory Variables: Using the level of digital financial development as a proxy indicator for model estimation, the results in Table 3 column (5) indicate that the impact of the DGE on CMP remained robust.

5.1.2. Endogeneity Test

(1) Dynamic SDM: The dynamic spatial panel model effectively controlled for the influence of unobserved variables by incorporating lagged variables and spatial effects. The lagged terms accounted for temporal autocorrelation, while spatial lag terms captured the associations between neighboring regions, thereby reducing biases caused by unobserved factors. Based on column (6) in Table 3, this study further examined the impact of the DGE on CMP using a dynamic SDM. Compared to column (3), the spatial effect of the DGE on CMP in column (6) remained consistent in terms of direction or significance; only the spatial effect coefficient decreased to 0.150.

(2) Instrumental Variable Method (IV): To address potential endogeneity due to omitted key explanatory variables and reverse causality during the estimation, we adopted the instrumental variable method and selected the number of city post offices in 1984 as the instrument for measuring the DGE. By employing this instrumental variable, estimated by Model (5) and with the results shown in Table 3 column (7), the results indicate that the spatial lag term W×DGE of the core explanatory variable was significantly positive. This finding further demonstrated the robustness of the model employed in this study.

5.2. Spatial Effect Decomposition

Comparing the coefficients ρ between the SLM and SDM, it was observed that the estimated ρ in the SDM was lower than in the SLM, suggesting that ignoring the spatial lag of the explanatory variables would overestimate the endogenous spatial interaction effects [85]. Therefore, the partial derivatives of the explanatory variables were calculated as a hypothesis test for the existence of spatial spillover effects.

Based on the estimation results in Table 3, this study further calculated the direct and spillover effects, as shown in Table 4. The coefficient for the impact of the DGE on CMP under the SDM direct effect was 0.048, which passed the 1% significance test. This indicates that an increase in the city's DGE development level promoted the city's CMP development. Under the spatial spillover effect, the DGE had a coefficient of 0.257, achieving significance at the 1% level, meaning that enhancing a city's DGE level helped promote the CMP development in its neighboring cities. Furthermore, comparing the DGE direct and spillover effect coefficients revealed that the regional spillover effect of the DGE on CMP was significantly weaker than the inter-regional spillover, demonstrating that the DGE indeed had spatial spillover effects on CMP development and providing empirical support for Hypothesis 1.

Observed from the direct effects parameter estimates of control variables, the ER and ED significantly improved the city's CMP level. However, in the spillover effects of both the SLM and SDM models, at the 1% level, the coefficient for the ED was found to be significantly negative. This indicates that as the development gap between geographically and economically adjacent cities increased, and the education level in neighboring cities had a negative impact on the city's CMP development through spillover effects. The reason for this is likely the significant differences in education quality among cities along the YRB due to geographic and economic constraints. Barriers were found to exist for the flow of educational resources such as teaching staff, school conditions, and educational funding across regions. Core cities were found to be prone to education resource siphoning effects, and the mechanism for equitable and high-quality development in compulsory education was found to need improvement. The integration of information technology with education was relatively low. The results for the ISE and IS did not show consistency across the two models.

Observed from the spillover effects parameter estimates of control variables, the ISE had a certain suppressive effect on the CMP of neighboring cities. This is likely due to the relative scarcity of emerging industry clusters in the midle and upper reaches of the YRB, where agriculture, raw materials, and energy chemicals have been predominant. Structural constraints on the transition from old to new drivers were found to be prominent, and cities exhibited varying levels of support for technology transfer, with resource-based industries undergoing insufficient and uneven transformation. The direct effect of the IS in the SDM was not significant, but the spillover effect was significantly positive at the 5% level, indicating that an increase in IS in a city promoted CMP development in its neighboring cities, with a clear spatial spillover effect.

Table 4. Direct and spillover effects of DGE on CMP.

Variables	Direct Effect		Spillover Effect	
	(1) SLM	**(2) SDM**	**(1) SLM**	**(2) SDM**
DGE	0.061 *** (2.84)	0.048 *** (2.66)	0.143 *** (2.67)	0.257 *** (2.78)
ISE	0.046 * (1.84)	0.001 (0.04)	−0.105 * (−1.94)	−0.208 * (−1.75)
IS	−0.002 (−0.55)	0.001 (0.30)	−0.005 (−0.54)	0.047 ** (2.09)
OP	0.010 (1.55)	0.007 (1.17)	0.022 (1.54)	0.001 (0.03)
ER	0.001 ** (1.98)	0.001 *** (2.72)	0.002 * (1.85)	0.003 (1.20)
FD	0.001 (1.34)	0.001 (0.65)	0.001 (1.27)	−0.006 (−1.51)
ED	0.001 *** (3.50)	0.001 *** (3.03)	−0.003 *** (−3.14)	−0.005 *** (−2.74)
SW	−0.058 (−0.85)	−0.066 (−0.98)	−0.135 (−0.81)	0.285 (0.53)
GI	0.001 (0.79)	0.001 (1.54)	0.001 (0.76)	0.001 (0.05)

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, with values in parentheses representing z-test.

5.3. Policy Shock

5.3.1. Parallel Trend Test

The core of BD policy lies in promoting the integration of data elements within and across regions, sharing big data infrastructure, fostering the deep application of big data, driving innovation in relevant systems and technologies, and cultivating talent in the big data industry [86]. The ultimate goal is to achieve coordinated development and share the benefits of big data. To evaluate the implementation effects of the BD policy, a parallel trend test was first conducted, with the results are shown in Appendix A in Figure A1. It was found that the regression results for the five periods before 2016 (the baseline year) were not statistically significant, although the coefficients showed an upward trend. After the implementation of the BD pilot policy, there was a positive effect on urban CMP, and the impact gradually increased over time. The sample met the parallel trend test criteria.

5.3.2. SDID Model Estimation

This study first used a traditional DID model to estimate the sample data, as shown in Table 5. The coefficient of the BD variable in Mod-1 was significant at the 10% level. In Mod-2, where control variables were added, the regression results failed to achieve statistical significance. Gravity distance Mod-3 and information distance Mod-4 added the spatial lag term of the BD policy dummy variable to the base of Mod-2. In both Mod-3 and Mod-4, the BD coefficients were significantly positive, indicating that the development of BD could advance the process of CMP in cities.

In the gravity distance Mod-3, the impact effect of W×BD was 0.178, passing the 1%significance test. This effect may have resulted from the BD policy's implementation, as the integrated application of digital technology spurred productivity growth, and its deep integration with the real economy enhanced economic development quality [19].

The weight matrix was further decomposed. In Mod-3, the coefficient of $W_{T,T}$×BD was significantly positive at 0.093, and the coefficient of $W_{NT,T}$×BD was significantly positive at 0.069. This indicates that the BD pilot policy not only promoted the development of CMP in the treatment group regions but also positively impacted the CMP process in the control group regions. The results of Mod-4 were consistent with those of Mod-3, further validating Hypothesis 1. Additionly, the coefficient of W×BD was found to be larger than that of $W_{T,T}$×BD + $W_{NT,T}$×BD, confirming that using the average utility tends to overestimate the spillover effect of the BD policy. Decomposing the W×BD effect provided a more robust validation of Hypothesis 1.

Table 5. Estimation results of DID and SDID.

Variables	DID		SDID	
	Mod-1	Mod-2	Gravity Mod-3	Information Mod-4
BD	0.235 * (1.72)	0.157 (0.41)	0.121 *** (6.96)	0.236 *** (2.77)
W×BD			0.178 *** (7.12)	0.188 *** (3.34)
$W_{T,T}$×BD			0.093 *** (9.46)	0.081 *** (4.15)
$W_{NT,T}$×BD			0.069 *** (9.40)	0.048 *** (4.64)
R^2	0.192	0.231	0.317	0.244
Control	NO	YES	YES	YES
City + Year FE	YES	YES	YES	YES

Note: *** and * indicate significance levels of 1% and 10%, respectively, with values in parentheses representing z-test.

5.3.3. Placebo Test

The SDID model in this study included time fixed effects and regional fixed effects. However, some cities might have experienced unobserved factors that changed over time. To exclude the interference of unobserved factors, a placebo test was conducted. The details in Appendix A in Figure A2 report the distribution of the estimated coefficients and p-values from 500 randomly generated treatment groups. The estimated coefficients and p-values were centered around zero, approximating a normal distribution and indicating that unobserved factors did not significantly affect the results. The model estimation results were not biased by omitted variables, and the construction of BD promoted urban CMP development. Thus, the external shock test further confirmed the robustness of the spatial impact effect of the DGE on CMP.

6. Further Analysis of the Spatial Impact of DGE on CMP

6.1. Spatial Boundaries of Spillover Effects

As the geographic distance between cities increased, communication and learning costs also rose, thereby reducing the likelihood of technological spillovers. Most studies have suggested that the spatial effects of technological spillover have certain regional boundaries [87]. However, as digital infrastructure construction accelerated, it facilitated resource sharing within digital clusters, creating digital channels for technology flow and knowledge dissemination [57].

The YRB represents one of China's major economic belts, with the spatial distribution of cities demonstrating significant clustering and hierarchical characteristics. Cities are densely distributed along the main course of the YRB, particularly in the middle and lower reaches, where several important urban clusters, including the Central Plains and Jiaodong clusters, have developed. In contrast, cities are sparsely distributed in the upper and more remote areas along the river basin. The average distance between cities in the YRB typically ranges from 50 to 200 km. Setting an interval of 50 km enabled a detailed analysis of the diffusion characteristics of DGE among densely populated urban clusters while maintaining observational accuracy in more sparsely populated areas and avoiding overly smoothed results. This study clarified the spatial decay characteristics of the spillover effects of the DGE on CMP. Within the 0–1500 km range, SDM regressions were conducted every 50 km using a gravity model-based spatial weight matrix, as shown in Table 6.

Table 6. Different spatial distance ranges of SDM spatial spillover effects.

Spatial Distance (km)	Spillover Effect DGE		Spatial Distance (km)	Spillover Effect DGE	
0–50	−0.014	(−0.57)	750–800	0.275 ***	(7.03)
50–100	−0.112 *	(−1.93)	800–850	0.305 ***	(5.28)
100–150	−0.128 **	(−2.10)	850–900	0.262 ***	(7.61)
150–200	0.052 *	(1.83)	900–950	0.212 ***	(6.18)
200–250	0.076 ***	(3.31)	950–1000	0.198 ***	(7.21)
250–300	0.166 ***	(3.63)	1000–1050	0.183 ***	(6.91)
300–350	0.144 ***	(4.12)	1050–1100	0.190 ***	(3.84)
350–400	0.201 ***	(4.76)	1100–1150	0.163 ***	(6.50)
400–450	0.454 ***	(6.48)	1150–1200	0.151 ***	(6.72)
450–500	0.340 ***	(6.56)	1200–1250	0.133 ***	(5.37)
500–550	0.418 ***	(8.11)	1250–1300	0.085 ***	(4.33)
550–600	0.476 ***	(10.01)	1300–1350	0.071 ***	(3.72)
600–650	0.479 ***	(12.18)	1350–1400	0.056 **	(2.44)
650–700	0.341 ***	(8.78)	1400–1450	0.049 **	(2.04)
700–750	0.311 ***	(6.31)	1450–1500	0.035 *	(1.88)

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, with values in parentheses representing z-test. Note2: Since the estimation results of the control variables were largely consistent with those in Table 3, and this section mainly examined the spillover effects of other cities' DGE development on the CMP of this city, Table 6 only reports the estimated spillover effects of the DGE index across various distance ranges.

Table 6 shows that the parameter estimates for the spillover effects of the DGE within the 50–100 km and 100–150 km were negative and statistically significant at the 10% level. When the spatial threshold exceeded 150 kilometers, the parameter estimates of the spillover effects were all positive and significant at least at the 10% level. This indicates that the lower boundary of the positive spatial spillover effect of the DGE on CMP in the YRB was 150 km. A possible explanation is that DGE development has connected "local-to-neighboring" cross-regional industries, breaking away from the high-cost model that has relied on traditional spatial proximity for industrial agglomeration. Through digital economy platforms, information exchange has enabled the cloud-based clustering of production factors, resulting in a more efficient "polarization" of capital. As the boundaries of regional markets have blurred and overlapped, the impact of the "competition effect" was amplified, intensifying the siphoning effect of DGE center regions on materials and other resources from surrounding underdeveloped areas. This also explained why large data centers could not coexist within the same region.

Additionally, the spillover effects of the DGE on CMP exhibited an inverted "U" shape with increasing spatial thresholds. Within the 150–600 km range, the spillover effect coefficients exhibited an upward trend, peaking at 0.479 between 600–650 km, before gradually declining. This range encompasses overlapping areas between the Yellow River Basin and other significant economic zones, such as the Yangtze River Delta and the Pearl River Delta. Therefore, the spillover effects of the DGE on CMP had significant spatial decay characteristics. Although the DGE could transcend spatial distribution factors through network effects, it was constrained by insufficient digital computing power and had not yet completed the transition from quantitative to qualitative development. Thus, its spatial spillover effects still exhibited geographical peaks. Hypothesis 1a was verified.

6.2. Spatial Heterogeneity

The YRB spans the western, central, and eastern regions of China, which exhibit significant differences in resource endowments, information infrastructure, economic and social development realities, and resource allocation. These disparities have led to the DGE's impact on CMP in the YRB exhibiting marked regional heterogeneity. Based on the gravity model spatial weight matrix, this study clarified the differences in the impact of the DGE on CMP among cities in the upper, middle, and lower reaches of the YRB[6]. The regional SDM estimation results are shown in Table 7.

The direct effect coefficients of the DGE in the three reaches were all significantly positive, indicating that the DGE promoted CMP in each basin. However, the DGE coefficient in the middle reaches was the smallest, confirming that the role of the DGE in advancing CMP in the YRB was uneven. The explanation provided is as follows: Although the cities in the middle reaches of the YRB had a relatively moderate level of industrial agglomeration and economic development, theoretically, the expansion of the DGE could have provided a strong impetus for their growth. However, the region's industries are predominantly based on raw materials and energy chemicals, facing significant pressures transitioning from old to new growth drivers. Additionally, the middle reaches of the YRB are characterized by ecological barriers and high-quality development, with severe challenges in soil and water conservation and forest and grass protection. The conflict between ecological and economic issues was found to be prominent, and the impact of DGE empowerment on regional economic development and social construction was found to be minimal. In contrast, the lower reaches of the YRB were found to have a strong foundation for DGE development. In contrast, the upper reaches, despite slower development, have benefited from national policy support, with the potential of digital factors being fully realized, effectively enhancing the incremental and amplification effects of the DGE.

Table 7. Spatial heterogeneity test.

Effect Type	Variables	(1) Upper-SDM		(2) Middle-SDM		(3) Lower-SDM	
Direct Effect	DGE	0.157 **	(2.27)	0.042 **	(2.26)	0.202 ***	(4.31)
	ISE	0.041	(0.88)	−0.142 **	(−2.52)	−0.389 ***	(−4.99)
	IS	−0.006	(−0.97)	0.029 ***	(2.87)	0.107 ***	(5.38)
	OP	0.016	(1.09)	0.003	(0.42)	0.007	(0.76)
	ER	−0.010	(−0.03)	0.001	(1.08)	0.006	(0.55)
	FD	0.005	(0.51)	−0.001	(−0.76)	−0.008 ***	(−2.92)
	ED	0.003	(0.24)	0.009 **	(2.16)	0.016 ***	(4.09)
	SW	−0.389 *	(−1.75)	−0.264 *	(−1.65)	0.038	(0.60)
	GI	0.011	(0.44)	−0.023	(−1.38)	0.001 **	(1.98)
Spillover Effect	DGE	0.030	(0.17)	0.116 *	(1.77)	−0.387 ***	(−2.63)
	ISE	0.433 ***	(3.09)	−0.128	(−0.48)	0.652 ***	(5.21)
	IS	−0.028	(−1.11)	0.060	(0.81)	−0.094 ***	(−2.67)
	OP	0.026	(0.45)	−0.050	(−1.11)	0.030	(1.14)
	ER	−0.002	(−1.58)	0.001	(0.27)	0.022	(1.20)
	FD	0.006	(1.40)	0.000	(0.04)	−0.021 ***	(−2.66)
	ED	0.001	(0.09)	0.014 ***	(3.03)	−0.007 ***	(−3.95)
	SW	0.207	(0.18)	0.774	(1.28)	−0.179	(−0.75)
	GI	−0.002	(−1.42)	0.002	(1.54)	0.004 ***	(2.90)
	ρ	0.424 ***	(4.85)	0.411 ***	(3.68)	0.460 ***	(6.69)
City + Year FE		YES		YES		YES	
Observations		242		275		319	
log-lik		601.6556		605.7249		742.9805	
R^2		0.2451		0.2309		0.2682	

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, with values in parentheses representing z-test.

In the lower reaches, the spillover effect coefficient of the DGE was −0.387, which was significant at the 1% level; in the middle reaches, the coefficient is 0.116 and significant at the 10% level; in the upper reaches, the coefficient was not significant. This indicates that the spatial spillover effects of the DGE's empowerment of CMP in the YRB exhibited clear regional heterogeneity. In conclusion, Hypothesis 1b was verified. The reason for this may have been that the core cities in the lower reaches of the YRB had a higher penetration rate of big data, industrial internet, and artificial intelligence into traditional industries. The close cooperation between government and enterprises across regions led to significant development advantages and a siphoning effect. The core cities have concentrated various factors of production due to their development advantages, causing relatively backward development in surrounding cities and limiting the positive spillover effects of DGE development. In the middle reaches, abundant coal resources have been used to address traditional overcapacity issues and reduce the dominance of coal. Supply-side structural reforms have been promoted, encouraging the upgrading of traditional industries. By relying on technological innovation and market mechanisms to optimize factor allocation, the region has promoted high-quality economic development. As a result, the core cities in the middle reaches had gathered a large number of innovative factors during their development, and these cities, relying on the spillover of some elements from the DGE, had empowered neighboring cities to achieve CMP. In the upper reaches, DGE development has still been in its early stages, with underdeveloped data infrastructure, and the benefits of the DGE have not yet been fully realized.

7. The Nonlinear Impact Effect of DGE on CMP

7.1. Nonlinear Test

The SPSTR model required checking whether there was a nonlinear relationship between the DGE and CMP before estimation and determining the number of location parameters. Hansen [88] and Luukkonental [89] used the first-order Taylor expansion of Equation (6) to construct an auxiliary regression equation to verify the existence of nonlinearity.

$$CMP_{it} = \mu_i + \beta_0^{T*}(DGE_{it}) + \beta_1^{T*}q_{it} + \cdots + \beta_m^{T*}DGE_{it}{q_{it}}^m + \mu_{it}^* \tag{10}$$

Here, $\mu_{it}^* = \mu_{it} + R_m\beta_1^T DGE_{it}$, where R_m represents the remainder term of the Taylor expansion; $\beta_1^* \cdots \beta_m^*$ are the multipliers of γ. Therefore, testing Equation (4) is equivalent to testing the null hypothesis $H_0^* = \beta_1^* = \cdots \beta_m^* = 0$ in Equation (10). In the auxiliary regression, pseudo-LRT statistics (LRTs), F-statistics (LMFs), and Lagrange multiplier statistics (LMs) were constructed and used for parameter testing. If the null hypothesis H_0^* is rejected, the model is nonlinear.

Table 8 presents the results of the LMs Test, LMFs Test, and LRTs Test. The linearity test in the first part of the table, where $H_0 : r = 0$ indicates that no transition function existed, and $H_1 : r = 1$ indicates the existence of one transition function, suggesting that the panel data exhibit nonlinear characteristics. Additionally, m represents the number of location parameters of the transition function, which is determined by the AIC and BIC criteria for m = 1 or m = 2.

For Mod-1, regardless of whether m = 1 or m = 2, all three tests rejected the null hypothesis $H_0 : r = 0$, indicating that the ISE had a nonlinear impact in the process of the DGE empowering CMP. Moreover, the LMs, LMFs, and LRTs tests did not reject the null hypothesis (H_0) when determining the number of transition functions r. Therefore, the ISE had one transition function. By comparing the AIC and BIC values for m = 1 and m = 2 was determined as the optimal number of location parameters, meaning the threshold value number was 1. For BPS, the test results were similar to those for ISE, indicating the presence of one transition function and one location parameter.

Table 8. SPSTR nonlinearity test.

Hypothesis Test	Test Type	Mod-1 (ISE) m = 1	Mod-1 (ISE) m = 2	Mod-2 (BPS) m = 1	Mod-2 (BPS) m = 2
Linear H_0:r = 0; H_1:r = 1	LM	90.274	138.052	104.898	154.122
	p-Value	(0.000)	(0.000)	(0.000)	(0.000)
	LMF	4.718	3.773	5.604	4.324
	p-Value	(0.000)	(0.000)	(0.001)	(0.000)
	LRT	96.102	152.351	112.881	172.246
	p-Value	(0.000)	(0.000)	(0.000)	(0.000)
Nonlinear H_0:r = 1; H_1:r = 2	LM	26.633	23.673	27.702	55.712
	p-Value	(0.114)	(0.967)	(0.032)	(0.089)
	LMF	1.198	0.514	1.211	1.266
	p-Value	(0.252)	(0.993)	(0.136)	(0.242)
	LRT	27.110	24.050	28.220	57.859
	p-Value	(0.102)	(0.962)	(0.020)	(0.079)
AIC		−7.941	−7.909	−7.927	−7.890
BIC		−7.697	−7.659	−7.640	−7.555

7.2. SPSTR Model Estimation

Table 9 presents the nonlinear estimation results of the spatial effects of the ISE and BPS in the process of DGE enhancing CMP. Figures 4 and 5 shows the transition function graph.

In Mod-1, the transition variable was the ISE, and there was one transition function. The transition function was divided into a linear effect β_0 and a nonlinear effect β_1 by the location parameter c (2.5338). Before crossing the threshold, the influence coefficient of each variable on CMP was β_0; after crossing the threshold, the influence coefficient became $\beta_0 + \beta_1$.

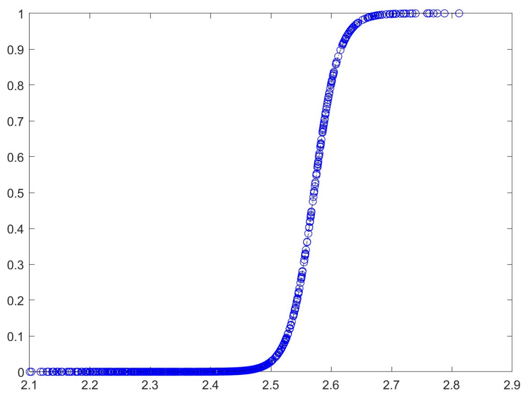

Figure 4. ISE transition probability plot.

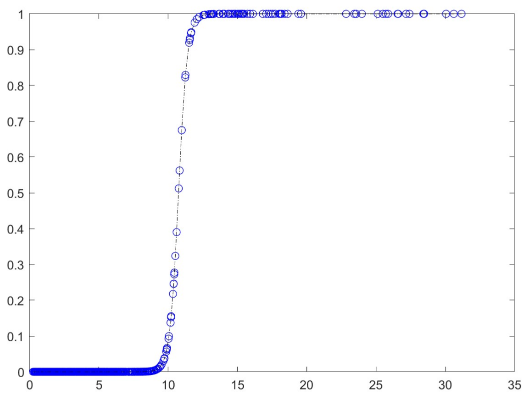

Figure 5. BPS transition probability plot.

Table 9. Estimation results of the SPSTR model.

Variables	Mod-1 (ISE)		Mod-2 (BPS)	
	β_0 (Linear)	β_1 (Nonlinear)	β_0 (Linear)	β_1 (Nonlinear)
DGE	0.0593 ** (2.1400)	0.3333 *** (3.5357)	0.0273 (0.6312)	0.4117 *** (2.9611)
ISE	−0.0161 *** (−3.9493)	0.1168 ** (2.1876)	−0.1437 (−1.4884)	0.4210 ** (2.2444)
IS	−0.0582 *** (−2.8936)	0.3377 *** (5.2912)	−0.0421 *** (−4.3233)	0.0648 *** (3.3134)
OP	0.0276 *** (3.7883)	0.5042 *** (3.4017)	0.0343 *** (4.1841)	−0.0428 * (−1.6463)
ER	0.0009 ** (2.4808)	0.0028 *** (2.8399)	0.0021 (1.5383)	−0.0031 (−1.5037)
FD	0.0001 (0.2345)	0.0041 (1.0232)	0.0165 *** (4.8996)	0.0187 *** (5.1864)
ED	0.0007 (0.6489)	0.0013 *** (2.9385)	−0.0001 (−0.0999)	0.0022 *** (10.7769)
SW	−0.0534 (−0.6493)	0.5801 (1.4730)	0.0248 (0.2244)	0.4657 ** (2.0244)
GI	−0.0002 (−0.3509)	−0.0043 (−1.1844)	−0.0003 (−0.8535)	0.0012 ** (2.3607)
W×CMP	0.0250 (0.3644)	0.7102 * (1.8553)	−0.0883 (−1.1789)	0.7688 *** (3.1863)
W×DGE	−0.1422 (−0.8684)	0.3591 *** (2.9775)	0.0967 (0.4876)	0.4563 *** (2.9696)
W×ISE	0.0963 (1.2322)	0.7657 * (1.9053)	0.0461 (0.4474)	−0.1045 (−0.5306)
W×IS	−0.0166 (−0.9422)	0.0211 (0.2351)	0.0009 (0.0366)	−0.0291 (−0.5801)
W×OP	−0.0066 (−0.3130)	−0.1068 (−0.9827)	−0.0310 (−1.1379)	0.0746 (1.2243)
W×ER	−0.0010 (−0.7177)	0.0139 * (1.6842)	−0.0017 (−0.9909)	0.0102 (1.1386)
W×FD	−0.0023 (−1.2204)	0.0194 (1.3563)	−0.0047 (−1.5351)	0.0056 (0.7513)
W×ED	−0.0003 (−0.4148)	0.0155 *** (2.9618)	−0.0393 (−0.7452)	0.2055 *** (3.1757)
W×SW	−0.2252 (−1.1103)	0.2857 (0.3257)	0.0373 (0.1379)	0.1042 * (1.8991)
W×GI	0.0004 ** (1.9901)	−0.0049 *** (−4.6362)	0.0003 (0.4453)	−0.0013 (−0.7118)
c	2.5338		10.3670	
γ	58.3816		3.8813	
RSS	0.204		0.248	

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively, with values in parentheses representing z-test.

Firstly, the linear part aligned with the SDM model estimation results, where the impact coefficient of DGE development was 0.0593, significant at the 5% level, indicating that DGE promoted CMP. The nonlinear part showed a DGE parameter estimate of 0.3926 (0.0593 + 0.3333), which was significant at the 1% level. As the industrial structure continued to evolve and the rationalization level was upgraded beyond the threshold, the DGE dividends were further released, leading to the digital reshaping of production relations and productivity. The cumulative effect of wealth creation was significantly enhanced, boosting the "making a bigger cake" multiplier effect, and it drove the trend of CMP development, exhibiting nonlinear marginal growth characteristics. The nonlinear impact coefficient of W×DGE was 0.2169 (−0.1422 + 0.3591), which was significant at the 1% level. This indicated that as the industrial structure was adjusted and reshaped, the depth and breadth of digital technology's influence increased. The DGE broke through spatiotemporal limitations and resource constraints of the traditional economy, enhanced the ability to bridge the "digital divide", and opened up new functionalities in cyberspace. This generated spatial spillover effects that empowered CMP. Hypothesis 2 was verified.

Secondly, the linear part of the parameter estimate for the IS was −0.0582, indicating that on the left side of the threshold, it had a significant negative impact on CMP. The nonlinear part showed a parameter estimate of 0.2795 (−0.0582 + 0.3377), indicating that on the right side of the threshold, the IS had a positive impact on CMP. This may have been because the primary task of achieving CMP has been to address the problem of unbalanced and inadequate regional development. To narrow regional disparities and achieve coordinated regional development, it is imperative to improve thr ISE's level. When the ISE level was low, the efficiency of industrial resource allocation and the coordination between industries were poor. If industrial upgrading was accelerated under these conditions, it could have exacerbated inefficient resource allocation. In the process of "deindustrialization" and "servicification", a situation of "structural inefficiency" may have emerged. Capital flowing into real estate and finance may have led to industrial hollowing [90], resulting in a shift away from real economic activities and hindering CMP development. When the ISE level was high and the industrial base was strong, with industrial upgrading, industrial organization and development models continued to innovate, the division of labor became more refined, and the technology and value chains underwent transformation and upgrading. This helped unleash the advantages of the domestic market, drove sustained income growth, and enhanced the "making a bigger cake" effect of overall prosperity.

Finally, when the level of the ISE was below 2.5338, the impact coefficient of W×GI was 0.0004, indicating a positive correlation between the degree of GI and CMP development. When the ISE level was above 2.5338, the impact coefficient of W×GI became −0.0045 (0.0004–0.0049), meaning that lower levels of GI significantly promoted CMP development. The possible reason was that the development of CMP required a shift in growth drivers and the optimization of the economic structure, with industrial structure evolution at its core. The rough and unrefined industrial structure urgently needed the coordinated efforts of market regulation mechanisms and government planning mechanisms to achieve rationalization and intensification. In the early stages of industrial structure rationalization, enhancing the market self-organizing capabilities, reforming the fiscal and tax systems, and removing market barriers could not be achieved without government involvement. At that stage, market mechanisms could not effectively function, requiring a "proactive government" to play a role in building systems and institutions; establishing a unified public platform [50]; and improving coordination mechanisms in infrastructure, institutions, and markets. This helped to boost demand, expand investment, promote industrial integration, and empower CMP. As industrial structure evolution progressed and rationalization levels improved, the market, under government support, developed a favorable business environment, a fair competition environment, and an open factor pricing mechanism. The market regulation mechanism became more autonomous, inclusive, and creative, with the "effective market" playing a leading role [91].

In Mod-2, the transition variable was the BPS, with a single location parameter c = 10.3670, which divided the transition function into a linear part β_0 and a nonlinear β_1, forming two smooth transition segments. The estimated parameters for W×DGE before and after transition were 0.0967 and 0.4563, respectively. The former did not pass the significance test, while the latter passed the 1% significance level test. Therefore, it can be inferred that when the BPS's level exceeded 10.3670, DGE development was conducive to promoting CMP. This confirmed that as the level of BPS improved, the foundational conditions in economically disadvantaged areas continued to optimize. This made it easier for marginalized groups, such as residents of remote cities and rural areas, impoverished populations, and low-skilled workers, to access digital resources and utilize digital technologies, leading to the equalization of development opportunities. The DGE's effects on poverty reduction, income growth, and inclusivity continually emerged, supporting balanced growth and enhancing the "dividing a better cake" effect of shared prosperity. Hypothesis 3 was verified.

The nonlinear estimation result for W×CMP was significant at the 1% level, revealing that the CMP's development in the YRB had a certain clustering effect in spatial terms. Optimizing resource allocation efficiency and promoting public service equalization could highlight spillover effects, shared benefits, and collaborative effects, fully leveraging the regional differences in CMP to achieve the goal of "leading the less prosperous" and "helping the less prosperous".

Further focusing on the control variables, the nonlinear impact of W×ED in the process of the DGE empowering CMP became more pronounced. When the BPS level was low, W×ED did not have a significant impact on CMP. However, once the BPS indicator crossed the threshold value of 10.3670, the W×ED coefficient reached 0.1662 (−0.0393 + 0.2055), which was significant at the 1% level. A core element in achieving the long-term goal of CMP was public service equalization, with educational equity serving as the foundation for social fairness. Quality education was crucial for securing income for the population [92]. The earlier the educational intervention, the better the outcomes [93]. For children from disadvantaged families, education played a critical role in improving personal life and expanding development opportunities. Enhancing the efficiency of public service provision and promoting the sharing of public service resources helped to reduce disparities in educational investment, dismantling administrative barriers to educational resources. This ensured the fair and reasonable distribution of high-quality educational resources, which could reduce income inequality, break down social class rigidity, and promote the achievement of CMP goals.

8. Conclusions and Policy Implications

8.1. Conclusions

This study, based on panel data from 2011–2021 at the prefecture-level cities in the YRB, scientifically measured the development indices of the DGE and CMP, using the SDM, SDID, and SPSTR models to empirically analyze the spatial impact effects, mechanisms, and heterogeneity of the DGE in empowering CMP. The main conclusions are as follows:

(1) The development pattern of the urban DGE exhibited a "downstream high, upstream low" characteristic, with cities in the lower reaches of the YRB generally having a higher level of DGE development compared to the upper reaches. The pattern of CMP development gradually shifted from a scattered distribution centered around provincial capital cities to a more regionally clustered state, with clear spatial dependence. The level of CMP in most cities steadily increased.

(2) The DGE's role in empowering CMP showed a significant spatial spillover effect. After introducing the BD policy as an exogenous shock, the conclusion remained robust. Considering spatial heterogeneity, the DGE in lower reaches cities had a significant empowering effect on CMP of the entire basin, but it had a suppressive effect on the CMP development within urban clusters. Based on the estimated spillover effect, the spatial spillover effect of the DGE on CMP peaked at the 600–650 km range.

(3) The ISE and BPS exhibited a significant single-threshold effect. The DGE drove CMP to achieve nonlinear growth by optimizing the industrial structure and promoting public service equalization, enhancing the "making a bigger cake" effect for overall prosperity and fostering the "dividing a better cake" effect for shared prosperity.

8.2. Implications

Based on the above research conclusions, the following implications are drawn:

(1) Grasp the DGE strategy and build a new engine for CMP. Use digital intelligence to support and lead the development of traditional industrial clusters in the YRB, facilitating the collaborative upgrading of resources, technological progress, and structural optimization, guiding industrial upgrading and optimization. Improve local accountability systems and policy frameworks, increase the supply of inclusive services, and leverage digital

technology to promote the sharing of public service resources. This enhances economies of scale, improves the efficiency and quality of public service delivery, and provides sufficient momentum for achieving CMP.

(2) Leverage the digital spillover effect to improve the industrial ecology of the basin. Strengthen regional technology sharing and cooperation, eliminate information technology barriers, and fully utilize the spatial spillover effects of the DGE to encourage equitable sharing of data resources. Implement appropriate preferential policies based on the specific conditions of urban clusters and metropolitan areas. Coordinate national big data pilot cities, guiding "data-rich areas" to provide preferential support to "data-scarce areas" located beyond 150 km. Facilitate the bidirectional flow of elements such as digital technology and digital capital, and reinforce the spatial spillover effects of the DGE.

(3) Clarify regional development characteristics and achieve CMP by adapting to local conditions. The spatial effects of the DGE in empowering CMP exhibit significant regional heterogeneity, requiring each region to formulate targeted policies based on its specific conditions. In the upper reaches, to avoid low-level repetitive construction, emphasis should be placed on planning the digital industry layout, attracting high-level talent, and strengthening independent innovation capabilities. The middle reaches should focus on addressing industrial homogeneity issues, emphasizing digital technology research and development, and transitioning the economic development model from resource processing to a technology-driven, environmentally friendly model. The lower reaches should focus on playing a leading role, integrating digital resources, strengthening industrial clusters in digital finance, technology R&D, and intelligent manufacturing, as well as establishing DGE pilot zones to promote coordinated regional development.

9. Limitations

(1) This study's assessment of CMP relied on static data, which limits the ability to dynamically monitor CMP and the instantaneous impact of the DGE. Our future work will focus on establishing a dynamic monitoring mechanism to track changes in the DGE in real time and provide precise guidance for CMP policies.

(2) China began publishing DGE-related data in 2011, resulting in the availability of certain tertiary indicators, such as IPV4, IPV6, big data centers, e-commerce transaction volume, and industrial internet patents, only from 2011 onwards. Therefore, the core indicator—the DGE index—started being measured from 2011 onwards, limiting the extension of the sample period to earlier years.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conffict of interest.

Appendix A

In Table A1, the evaluation indicator system for achieving CMP includes eight secondary indicators:

Table A1. CMP Process/Outcome Indicators.

Level 3	Index Interpretation	Data Source
Per capita GDP	/	Prefecture-level city statistical Yearbook
Labor productivity	GDP/Annual Average Number of Employees.	
R&D/GDP	/	
Invention patents/10,000 individuals	/	State Intellectual Property Office
Engel coefficient	Household Food Expenditure/Consumer Expenditure.	Prefecture-level city statistical Yearbook
Contribution rate of household consumption	Household Final Consumption/GDP.	
Per capita disposable income	Disposable income of residents/Permanent resident population.	
Labor compensation/GDP	/	
Treatment rate of sewage treatment plants	Sewage treatment capacity/total sewage discharge.	
Carbon emissions/GDP	/	Survey data
Energy consumption/GDP	/	
$PM_{2.5}$ concentration	Actual monitoring data.	Prefecture-level city meteorological Bureau
Per capita green space area	Total Urban Public Green Space/Urban Nonagricultural Population.	Prefecture-level city statistical Yearbook
Greening coverage rate	Total Vertical Projection Area of All Urban Green Planting/Urban Area.	
Air quality index	Proportion of days with good air quality.	Prefecture-level city meteorological bureau
Per capita library collection	Number of books in public libraries/population.	Prefecture-level city statistical Yearbook
Employees in the cultural industry total amount	Number of people employed in culture-related industries/average number of employees per year.	Survey data
Total hospital beds and doctors/10,000 individuals	/	Prefecture-level city statistical Yearbook
Intensity of education expenditure	Education spending/GDP.	
Road mileage/10,000 individuals	(Road mileage + railway mileage)/10,000 population.	
Public transport vehicles/10,000 individuals	Public transport vehicles/10,000 individuals.	
Per capita housing area	Total floor area/total population.	
Housing price/Per capita disposable income	/	CEIC database
Average wage disparity across industries	The Logarithmic Deviation Mean Index (MLD) is used to measure industry wage rate differentials and reinvented into the following form $MLD = \left\lvert \frac{1}{m} \sum_{h=1}^{m} \ln \frac{\bar{\omega}}{\overline{\omega_h}} \right\rvert$ Here, m represents the number of industry categories, $\bar{\omega}$ denotes the overall average wage level for all industries in prefecture-level city i, and $\overline{\omega_h}$ indicates the average wage level for industry h in prefecture-level city i. Referring to the classification standards of China's national economy (Document code issued by the State Council of China: GB/T 4754-2017), this study selects the average wages of employees across 19 industry categories, excluding international organizations, to construct the MLD index. A higher MLD index indicates greater wage disparities across industries, while an MLD index approaching zero suggests smaller wage differences.	Survey data
Healthcare coverage disparity across industries	Medical Security Expenditure in This Region/Medical Security Expenditure in the Region with the Highest Expenditure. Medical security expenditure = number of participants in basic medical insurance × financial subsidy standard + financial allocation for medical assistance.	

Table A1. *Cont.*

Level 3	Index Interpretation	Data Source
Urban–rural development disparity coefficient	$\alpha_i = \sum_i^n \frac{c_i - r_i}{n f_i}$ Here, n represents the number of cities in the YRB, f_i denotes the per capita disposable income of city i, c_i represents the per capita disposable income of urban residents, and r_i represents the per capita disposable income of rural residents in city i.	Prefecture-level city statistical Yearbook
Urban–rural education gap	Years of Education for Urban Residents-Years of Education for Rural Residents.	
Urban–rural employment burden ratio	(Urban Population − Rural Population)/Total Number of Social Workers.	Statistical Bulletin
Urbanization rate	Total Number of Social Workers.	
Income disparity coefficient	Urban Population/Total Population.	Prefecture-level city statistical Yearbook
Prosperity intensity index	$F_i = \frac{f_i}{d_i} \times \frac{e_i}{g_i}$ Here, g_i and e_i represent the GDP and fiscal revenue of city i, respectively, with their ratio indicating the government prosperity; d_i and f_i represent the per capita GDP and per capita disposable income of city i, respectively, with their ratio indicating the individual prosperity; F_i represents the overall prosperity.	
Regional development disparity coefficient	Theil coefficient.	
Disparity in basic public services across regions	Basic Public Service Expenditure in This Region/Basic Public Service Expenditure in the Region with the Highest Expenditure Based on the National Basic Public Service Standards (2023 Edition), combined with the 14th Five-Year Plan for Public Service and the 2023 Government Revenue and Expenditure Classification Subjects, the expenditure on culture, media, sports and tourism, urban and rural community affairs, and affordable housing are collectively defined as the expenditure on basic public services, and the proportion and sum of the above expenditures in the general public budget expenditure are taken as the measurement indicators of basic public service expenditure.	Survey data

Efficiency Improvement: Labor productivity better reflects the progress of social production than GDP growth alone, with per capita GDP serving as an important reference for assessing living standards.

Innovation Driven: Focuses on the "technology powerhouse" and "Digital China" strategies, primarily examining R&D investment and the number of invention patents.

Structural Optimization: The contribution rate of consumption is linked to the "dual circulation" strategy, while the Engel coefficient indicates improvements in residents' quality of life.

Income Security: In line with the 19th National Congress report's call to "ensure that residents' income grows in tandem with economic growth and that labor remuneration increases alongside labor productivity", the emphasis is on monitoring growth in household income and labor compensation. Energy Conservation: The development level of infrastructure is reflected in the wastewater treatment rate, while reductions in energy consumption and carbon emissions per unit of GDP align with China's new requirements for industrial upgrading, carbon neutrality, and carbon peaking.

Ecological Quality: Primarily reflects public concerns regarding $PM_{2.5}$ concentration, air quality, and green space area.

Cultural Literacy: With improvements in material living conditions, people's demand for a richer spiritual life have increased, presenting opportunities for the cultural industry. The number of library books and employment in cultural industries reflects advancements in meeting residents' cultural and spiritual needs.

Quality of Life: The tertiary indicators captures residents' aspirations for a better life, demonstrating foresight and specificity. Healthcare: Uses the number of practicing physicians and the number of elderly care beds as combined indicators to address the future aging society and the development of a more advanced healthcare system. Education:

Education expenditure intensity indicates the level of national investment in education. Transportation: Indicators such as the number of public transport vehicles and the mileage of roads and railways per 10,000 people reflect the construction of the public transportation system. Housing: Aligns with the desire for "affordable and comfortable living", using the housing price-to-income ratio and per capita living space as indicators.

The evaluation indicator system for the outcomes of CMP places greater emphasis on "equity", focusing on the extent of shared development across various dimensions. This emphasis is primarily reflected in the continuous narrowing of disparities among different population groups, urban and rural areas, income levels, and regions. The differences among populations primarily reflect disparities in industry wages and healthcare coverage. The urban–rural differences manifest in four aspects: employment, education, income, and governance. Income differences indicate the material wealth status of residents and individual income gaps. Regional differences include income disparities between regions and variations in basic public expenditures, such as those for cultural and recreational activities, community services, and affordable housing.

Table A2. DGE Indicators.

Level 3	Index Interpretation	Data Source
Internet broadband access ports/Population	Number of Internet Broadband Access Ports per Capita.	Municipal Statistics Bureaus
Mobile phone users/100 individuals	/	
Mobile phone base stations total amount	/	
IPV4/IPV6	/	Survey data
Big data centers	/	
Revenue from telecommunications and postal services	Telecommunications Revenue = ∑ (Business Volume of Various Telecommunications Services × Corresponding Service Fees) + Revenue from Leasing, Maintenance, and Other Services.	Statistical Bulletin
	Postal Service Revenue = ∑ (Business Volume of Various Communication Services × Corresponding Service Fees) + Revenue from Leasing, Maintenance, and Other Services.	
Employees in information and software services's number	/	Municipal Statistics Bureaus
Number of listed companies in intelligent manufacturing	The registered locations of listed manufacturing companies are recorded, and their annual reports are examined for mentions of intelligent-related terms such as artificial intelligence, big data, cloud computing, and blockchain. The findings are then aggregated at the city level.	Wind database CSMAR database
Listed ICT companie's number	/	Survey data
E-Government service platforms	/	Statistical Bulletin China E-Government Development Report
E-Commerce transaction volume	/	
Industrial internet patents granted total amount	/	China National Intellectual Property Administration

Table A2. *Cont.*

Level 3	Index Interpretation	Data Source
Penetration rate of digital high-tech applications	The penetration level is determined by calculating the frequency of mentions of digital technologies such as artificial intelligence, big data, cloud computing, and blockchain, along with their related sub-indicators, in the annual reports of industrial listed companies. These frequencies are then averaged and aggregated at the city level.	Wind database CSMAR database
Density of industrial robot installations	The installation figures for industrial robots across various industries in China, as published by the IFR Alliance (covering 14 major categories corresponding to the sub-industry codes 13–43 in the National Economic Industry Classification and Codes released in 2017 [Document code issued by the State Council of China: GB/T 4754-2017]), are used. The percentage of employment in each sub-industry by city, relative to the national total, is then collected from the China Labor Statistical Yearbook. This percentage is multiplied by the total number of robot installations in each industry nationwide.	International Federation of Robotics (https://ifr.org/) China Labor Statistical Yearbook.

First, Digital Element Driven. Digital element provides essential technological support for digital development, serving as the foundation of the DGE and society. Five specific indicators are chosen: the number of internet broadband access ports per capita, the number of mobile phone users per 100 people, the number of mobile phone base stations, IPV4/IPV6, and the number of big data centers.

Second, Digital Industrialization. It serves as the foundation and primary driving force behind the development of the DGE, encompassing economic activities that provide digital technology, products, services, infrastructure, and solutions for industrial digitalization, as well as various industry activities entirely dependent on digital technology and data elements. Based on the definition of digital industrialization in the "Four Modernizations" framework by the China Academy of Information and Communications Technology, and considering data completeness and availability, the indicators chosen to represent the development of digital industrialization include telecommunications and postal service revenue, the number of employees in software and information services, the number of listed intelligent manufacturing companies, and the number of listed ICT companies.

Third, Industrial Digitization. As a core area of DGE development, it refers to the comprehensive transformation of traditional industries through modern information technology. Five indicators were chosen to represent this dimension: e-government service platforms, e-commerce transaction volume, the number of industrial internet patent authorizations, the penetration level of digital high-tech applications among listed companies, and the installation density of industrial robots. These indicators provide a means to depict the levels of service sector digitalization and industrial digitalization to a certain extent.

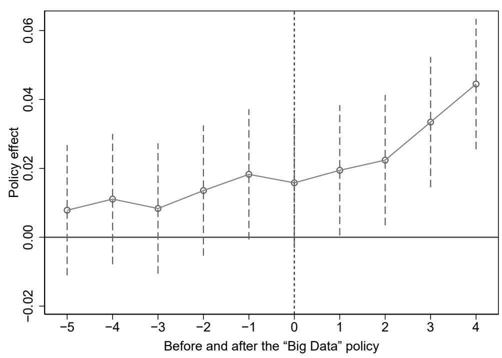

Figure A1. Results of parallel trend test. Note: The horizontal axis in Figure A1 represents the number of years relative to 2016.

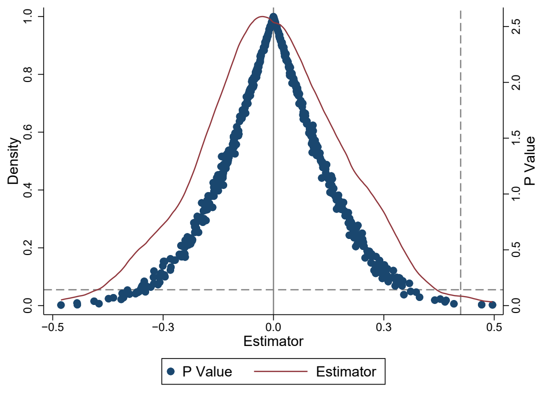

Figure A2. Results of placebo test.

Table A3. Moran's I index of DGE and CMP.

Year	CMP			DGE		
	Mor-Index	Z-Sta	*p*-Val	Mor-Index	Z-Sta	*p*-Val
2011	0.111 ***	2.690	0.007	0.123 ***	3.997	0.000
2012	0.144 ***	3.391	0.001	0.133 ***	3.446	0.001
2013	0.138 ***	3.263	0.001	0.146 ***	3.446	0.001
2014	0.163 ***	3.818	0.000	0.148 ***	3.523	0.000
2015	0.151 ***	3.539	0.000	0.186 ***	4.386	0.000
2016	0.160 ***	3.749	0.000	0.220 ***	5.128	0.000
2017	0.175 ***	4.082	0.000	0.212 ***	4.901	0.000
2018	0.192 ***	4.422	0.000	0.208 ***	4.831	0.000
2019	0.201 ***	4.635	0.000	0.220 ***	5.161	0.000
2020	0.201 ***	4.634	0.000	0.220 ***	5.172	0.000
2021	0.204 ***	4.813	0.000	0.223 ***	5.241	0.000

Note: *** indicates a 1% significance level.

Table A4. Spatial model selection test.

Test	Statistic
LM (lag) test	27.3196 ***
Robust LM (lag) test	30.4185 ***
LM (error) test	11.5161 ***
Robust LM (error) test	12.4335 ***
Hausman test	42.9203 ***
Wald_spatial_lag	36.1757 ***
LR_spatial_lag	28.1102 ***
Wald_spatial_error	42.7058 ***
LR_spatial_error	31.0303 ***

Note: *** indicates a 1% significance level.

Notes

1 The primary industry mainly refers to agriculture, forestry, animal husbandry, and fishery industries. The secondary industry refers to mining (excluding mining auxiliary activities); manufacturing (excluding metal products and machinery and equipment repair); the production and supply of electricity, heat, gas and water; and construction. The tertiary industry, namely, the service industry, refers to other industries other than the primary industry and the secondary industry. The source is China's National Bureau of Statistics.

2 According to the division by the Yellow River Conservancy Commission of the Ministry of Water Resources, the YRB flows through nine provinces: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi, Henan, and Shandong. In this study, several factors were considered, including the "YRB Ecological Protection and High-Quality Development Plan" and the YREB development strategy, administrative boundary adjustments, and data gaps. Cities that had been integrated into the YREB

were excluded, including Laiwu City, which had been merged into Jinan, and areas with missing data, such as Jiyuan City in Henan Province, Yushu Tibetan Autonomous Prefecture, Gannan Tibetan Autonomous Prefecture, and Linxia Hui Autonomous Prefecture. Ultimately, 76 cities along the YRB in eight provinces were selected as the research sample.

[3] In August 2015, China's State Council issued the "Action Plan for Promoting Big Data Development", which explicitly called for "regional pilot programs to advance the construction of Big Data Comprehensive Experimental Zones". In 2016, the construction plans for Big Data Comprehensive Experimental Zones in regions such as Beijing-Tianjin-Hebei, the Pearl River Delta, Shanghai, Henan, Chongqing, Shenyang, Inner Mongolia, and Guizhou were officially approved".

[4] Given the broad geographical scope, data limitations, and generalizations of this study, a weight matrix based on geographical distance and GDP scale was selected. This approach is more suitable for capturing spatial interactions between different regions. In the robustness test, the matrix representing the information development level was also considered to ensure the robustness of the conclusions.

[5] The formula for information distance is $W_1 = A_{it}B_{jt}/d_{it}$, A_{it}, B_{jt}, which represents the per capita number of international internet users in cities i and j in period t, respectively, and d_{it} represents the geographical distance between cities i and j.

[6] The YRB can be divided into three major regions based on its natural boundaries. The upper reaches include all of Ningxia; most cities and prefectures of Qinghai, Gansu, and Inner Mongolia; the middle reaches that include all cities of Shanxi, most of Shaanxi, and a few cities in Gansu and Henan; and the lower reaches that include parts of Shandong and Henan.

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