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Research on the Impact of Data Elements on the Modernization Level of Industrial Chains

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Abstract

Based on panel data from 30 Chinese provinces between 2010 and 2021, this study empirically examines the impact of data factor allocation levels on industrial chain modernization and its underlying mechanisms from multiple perspectives. The results demonstrate that data factor allocation significantly improves the level of industrial chain modernization. This conclusion remains robust after addressing endogeneity concerns. Further research reveals that data elements promote industrial chain modernization by alleviating labor factor misallocation. Regional heterogeneity analysis indicates that data factors exhibit substantial effects in eastern China, while their influence remains underdeveloped in central and western regions. Finally, relevant policy recommendations are proposed to optimize these mechanisms.

Keywords: data factors, China's industrial chain modernization, resource misallocation index

1. Introduction

According to the data provided in the Industrial Base Index (2022) report, it can be seen that in 2022, China's manufacturing value-added will account for nearly 30% of the global scale, reflecting the country's great potential and international influence in the manufacturing sector. However, compared with the huge manufacturing scale, China is still weak in terms of industrial basic R&D capability and manufacturing strength. Especially in the high-end basic components, core components and other key areas, its import dependence is as high as more than 90%. Further analyzing the current situation of China's manufacturing industry, we can see that the layout of the industrial chain is not balanced phenomenon is prominent. The lack of effective articulation and synergy between various links leads to irrational resource allocation and low efficiency. The pace of industrial chain upgrading is also relatively slow, unable to adapt to the trend of rapid changes in market demand. Together, these problems constitute the status quo of China's weak industrial foundation, making it difficult to meet the needs of high-quality development of the domestic economy. In recent years, with the booming development of the digital economy, data elements, as the core elements of the digital economy, play a more important role in digitization to promote the development of the industrial chain. However, the existing value chain theories and statistical approaches do not pay enough attention to the role of intangible assets in the industry chain with data assets as the core. This paper is based on this background to explore the impact of the data factor allocation level on the modernization of the industrial chain.

2. Journals Reviewed

Zhang Hu's (2023) research shows that in the modern economic system, the trend of social division of labor and specialization has become more and more obvious. This division of labor is not only reflected in the vertical integration of traditional industries, the industrial chain is further refined and specialized, and each link is closely connected with other links, constituting an interdependent chain. However, this specialized and refined industrial division of labor also brings new problems. Due to the accelerated speed of information transmission, various factors of production flow rapidly within the industrial chain, resulting in the industrial chain becoming more intricate and complex. In such an environment, the transaction costs between the upstream and downstream of the industrial chain have greatly increased, restricting the development of the industrial chain. In this regard, Li Xiaohua and Wang Yifan (2020) point out that in the wave of the digital economy, all links of the industrial chain have been digitized. Data, as a new production factor, is no longer limited to the internal departments of enterprises, it has crossed the border and started to circulate between vendors at different levels of the industrial chain. This free flow of data elements greatly improves the synergistic efficiency of the industry chain, promotes the optimal allocation of resources and the release of innovation capacity, and thus promotes the upgrading and transformation of the whole industry chain.

Traditionally, the industrial chain is divided into two types: buyer-driven and producer-driven. Purchaser-driven industrial chains are mainly driven by consumers, while producer-driven industrial chains rely on technological progress and efficiency improvement in the production process to drive value creation. However, with the rise of large digital platform-based enterprises, the mode of operation of the global industrial chain has changed drastically. Daniel (2022) points out that these enterprises are able to lead the industrial chain change mainly due to their possession of a large amount of intangible assets such as data, software, and brands. These intangible assets constitute their competitive advantages and make them significantly different from previous chain "owners" in terms of value creation. Sudheer (2022) further elaborates that e-commerce platform enterprises have utilized their powerful platform effect to achieve rapid market expansion by means of lowering transaction costs and reducing information friction. that achieve rapid market expansion. They attract users through user participation mechanisms, thus effectively capturing the market share of traditional dealers. These emerging industry chain "chain masters" will continue to lead the new direction of the industry chain, and at the same time bring great opportunities and challenges to all participants. Zhu Ocean (2024) points out in his research that the circulation and trade of data elements in the international arena has achieved remarkable results, and this progress signifies that the circulation and trade of data elements in China is stepping into a completely new stage of development. However, China faces many challenges in this area. These include a series of problems such as insufficient domination by state-owned enterprises, ambiguous business models, low level of technology application, unclear rules and standards, incomplete construction of security systems, and lack of market regulation.

Existing research has laid an important foundation for understanding the relationship between data factors and industry chain modernization, but there are still the following areas to be deepened: First, as a new type of production factor explicitly put forward by the state, there are not many relevant studies, and empirical research is even more insufficient, this paper tries to explore to make up for the shortcomings in the field of data factor research. Secondly, the existing literature focuses on the direct role of data factors in improving the efficiency of the industrial chain, and the mechanism of "how data factors promote the modernization of the industrial chain through the optimization of factor allocation" is not sufficiently explored, especially the lack of attention to the problem of mismatch of traditional factors, such as labor, capital, and so on; thirdly, the literature has discussed the spatial heterogeneity of data factors, and has also discussed the importance of data factors. Third, the existing literature on the spatial heterogeneity of data factors mostly stays at the level of status quo description, especially the lack of empirical tests on the moderating role of regional factor endowments; fourth, the existing literature on the spatial correlation characteristics of data factors is insufficient. The marginal contributions of this paper are: (1) constructing the theoretical framework of "data factor-resource reallocation-industry chain upgrading" under the perspective of factor mismatch, and revealing the conduction path of the influence of data factors on the modernization of the industry chain; (2) adopting the instrumental variables method and the dynamic spatial Durbin model to deal with the endogeneity and spatial spillover effects, and reveal the role of data factors on the modernization of the industry chain. factors on industrial chain modernization; (3) analyze the regional differences and sources of the influence of data factors on industrial chain modernization in China, reveal the spatial and temporal evolution characteristics of industrial chain modernization, and provide empirical evidence for the implementation of differentiated regional data factor allocation policies.

3. Theoretical Analysis and Research Hypotheses

Data elements are non-exclusive, that is, the use of data elements does not exclude the use of others. This characteristic allows data elements to be accessed and used by enterprises in each industrial chain link at low cost, thus promoting the modernization of the industrial chain. Yuan Chun et al. believe (2021) that the application of digital technology in the industrial chain can improve the competitiveness and overall efficiency of the industrial chain. By reducing search costs, communication and negotiation costs, production costs, and improving default costs, digital technology brings all-round optimization and enhancement to the industrial chain. Li Chunfa et al. (2020) pointed out in their study that digital information has become a "standardized" circulation medium in the industrial chain. As a new type of production factor, data factor reshapes the traditional industrial chain structure. The data factor breaks down the information barriers between industrial chain subjects, and the real-time interaction between enterprises, suppliers, distributors and consumers forms an accurate supply and demand matching network. This data-driven precise decision-making mechanism not only builds up the dynamic synergy system of the industry chain, but also generates the multiplier effect of production factors through the data sharing mechanism, which qualitatively improves the operating efficiency of the industry chain ecosystem.

Hypothesis 1: The allocation level of data factors has a positive impact on the modernization level of the industrial chain.

The synergistic effect of data factors and traditional production factors such as capital and labor means that data factors are combined with capital and labor to improve production efficiency and product quality through technological innovation and business model innovation, and promote the modernization of the industrial chain. Lian Yuanmei et al. believe (2024) that industrial modernization is reflected at the level of industrial form as an industrial network system formed by the close horizontal and vertical linkage and fusion coordination of industries, and data elements can guide the integration of elements with the interweaving and fusion of digital space and physical space to provide an environmental basis for the construction and evolution of industrial network systems. It provides a new way to gather resources and organize coordination, and promotes the integration of elements across time and space. Wu Xiaoxu and Ren Bao ping (2022) argue that data elements promote the flexibility and efficiency of labor resource allocation by eliminating time and space barriers, realizing distributed employment and the emergence of new employment forms, such as digital microbusiness and Internet net work. In addition, the digital economy improves the efficiency of capital allocation by enhancing the flexible accumulation of capital and improving the matching of supply and demand, and facilitates the in-depth integration of the virtual and real economies. Through data intelligence and network collaboration, it improves the capital allocation mechanism and reduces information asymmetry, thus increasing the allocation efficiency of credit resources.

Hypothesis 2: The level of data allocation positively affects the optimization and upgrading of the industrial chain by suppressing the capital mismatch index and the labor mismatch index.

To summarize, data elements, through the above mechanism, can produce a chain reaction within the industrial chain and enhance the overall level of the industrial chain, and this enhancement will also spread beyond the industrial chain and produce a positive spillover effect on related industries and even the entire economic system. Therefore, giving full play to the role of data elements is of great significance in upgrading the industrial chain and building a modernized economic system.

4. Model Design and Variable Description

4.1 Data sources

In this paper, the panel data of 30 provincial-level administrative regions in China (excluding Tibet Autonomous Region, Hong Kong, Macao and Taiwan, as their data are not available) from 2011 to 2021 are selected as the research object. The data are mainly obtained from China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Science and Technology Statistical Yearbook and China Internet Development Statistical Report in previous years, and supplemented by visiting the official websites of relevant provincial statistical bureaus.

4.2 Variable Selection and Description

4.2.1 Interpreted Variables

This paper draws on the research of Zhang Hu et al. (2022) to construct the explanatory variables from the dimensions of industry chain foundation, industry chain digitization, industry chain innovation, industry chain resilience, industry chain synergy, and industry chain sustainability, which can reflect the level of progress in industry chain modernization in each province of China over a period of time. It reflects the optimization and upgrading of the industrial structure, the improvement of the industrial technology level, and the upgrading of the industrial chain in each province. This data reveals the differences and characteristics of Chinese provinces in promoting the process of industrial modernization.

4.2.2 Core Explanatory Variables

The level of data factor allocation cannot be measured by a single indicator, so this paper draws on the methodology of Li Zhi guo et al. (2021) to construct indicators to measure the level of data factor allocation from the dimensions of data factor management, data development and application, data dissemination and sharing, and data application environment.

4.2.3 Mediating Variables

The factor mismatch index specifically includes the capital mismatch index (tauk) and labor (taul) mismatch index, this paper draws on the research of scholars such as Bai Junhong et al. (2021) to compute the capital mismatch index and the labor mismatch index at the provincial level, and the computational formulas are as follows:

$$taul = \frac{1}{1+\gamma_{Ki}}, tauk = \frac{1}{1+\gamma_{Li}} \tag{1}$$

Among them, γ_{Ki} and γ_{Li} represent the capital and labor price distortion coefficients, respectively, and are calculated as follows:

$$\gamma_{Ki} = \left(\frac{K_i}{K}\right) / \left(\frac{s_i\beta_{Ki}}{\beta_K}\right), \gamma_{Li} = \left(\frac{L_i}{L}\right) / \left(\frac{s_i\beta_{Li}}{\beta_L}\right) \quad (2)$$

Among these, s_i denotes the share of output from province i in the total economic output, K_i /K denotes the share of capital used by province i in the total capital stock, $s_i\beta_{Ki}/\beta_K$ represents the proportion of capital used by province i when capital is effectively allocated, β_{Ki} is the capital-output elasticity estimated through the production function for each province, γ_{Ki} reflects the degree of capital misallocation; L_i /L denotes the share of labor used by province i in total labor, $s_i\beta_{Li}/\beta_L$ represents the proportion of labor used by region i when labor is efficiently allocated, β_L is the labor-output elasticity of each province estimated using the production function, and γ_{Li} reflects the degree of labor misallocation.

4.2.4 Control Variables

This paper introduces the following variables as control variables based on existing literature. Government intervention level (gov): the ratio of general public budget expenditure to regional GDP; foreign direct investment (fdi): the ratio of actual foreign investment to regional GDP. Educational level (highedu) refers to the student-to-faculty ratio in regular universities; infrastructure development (incon) refers to the per capita actual urban road area at the end of the year; urbanization level (urate) refers to the proportion of urban population in the total resident population; technological progress (tech) refers to the logarithm of the number of authorized patents in the region; economic development level (eco) refers to the logarithm of per capita actual GDP in each region; environmental regulation (ft) refers to the ratio of actual investment in industrial pollution control to industrial total output value.

4.3 Model Construction

To explore the impact of data element configuration levels on industrial chain modernization, this paper establishes the following panel model:

$$\text{Ind}_{it} = \alpha_0 + \alpha_1\text{data}_{it} + \alpha_2\text{control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In this equation, i represents region, and t represents time. Ind_{it} represents the level of industrial chain modernization in the region; $data_{it}$ represents the level of data element allocation; $control_{it}$ represents the control variable. $\mu_i$represents the individual effect, λ_t represents the time effect, and ε_{it} represents the random error term.

5. Empirical Analysis

5.1 Benchmark Regression Results

This paper employs a panel fixed-effects model for estimation. Table 1 reports the benchmark regression results on the impact of data element allocation levels on industrial chain modernization. Column (1) shows that the coefficient of the core explanatory variable is significantly positive at the 1% level. Column (2) further incorporates control variables, and the coefficient decreases due to the removal of unobservable factors related to industrial chain modernization, but remains positive and statistically significant at the 1% level. The empirical results consistently indicate that improving data element allocation levels helps promote provincial industrial chain modernization.

Table 1. Baseline regression results

	(1)	(2)
	Ind	Ind
data	0.392***	0.341***
	(0.087)	(0.092)
constant term (math.)	0.050***	0.331
	(0.009)	(0.321)
sample size	330	330
control variable	uncontrolled	containment
time effect	containment	containment
province effect	containment	containment
R2	0.925	0.950

Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively; numbers in parentheses are standard errors. The following table is the same.

5.2 Endogeneity Discussion

The benchmark regression results indicate that improvements in data element allocation have a significant promotional effect on industrial chain modernization, with the two exhibiting a significant positive correlation. However, it is important to note that the model may suffer from endogeneity bias. As the level of data element allocation increases, the level of industrial chain modernization may impose higher requirements on the use of data elements, potentially leading to a reverse causal relationship between industrial chain structure and data element allocation levels. To eliminate this endogeneity effect, following the research of Huang Yong chun (2022), the interaction term between the number of post offices in 1984 and the lagged number of internet users per 100 people is used as an instrumental variable. Additionally, a two-stage regression is conducted using an instrumental variable combination that includes a lagged term for data element allocation. Table 2 confirms that the core conclusions are not affected by endogeneity issues.

Column (1) presents the regression results using the lagged value of data element allocation as the instrumental variable, while Column (2) uses the interaction term between the number of post offices in 1984 and the lagged number of internet users per 100 people as the instrumental variable. The results show that, even after accounting for endogeneity, the coefficient for the level of data element configuration remains significantly positive, consistent with the benchmark regression results in the table below. This further demonstrates that improving the efficiency of data element configuration contributes to enhancing the modernization of the industrial chain.

Table 2. Analysis of regression results for instrumental variables

	Ind(1)	Ind(2)
data	0.283*** (0.052)	0.104** (0.047)
Time effect, province effect control variable	containment	containment
Kleibergen-Paap rk LM	30.717 [0.000]	52.643 [0.000]
Kleibergen-Paap rk Wald F	203.485 {9.080}	135.162 {16.380}
sample size	300	330
Phase I	1.105*** (0.122)	3.11e-06*** (2.67e-07)

Note: Numbers in () are standard errors, numbers in [] are p-values, and numbers in {} are critical values for the Stock-Yogo weak discrimination test at the 10% level.

5.3 Robustness Tests

To verify the rigor of the empirical results, this paper conducts robustness tests from the following two aspects: first, this paper regresses the core explanatory variable lagged by one period, with the results shown in Table 3; second, this paper establishes a dynamic panel model for estimation, with the results shown in Table 4. It can be seen that regardless of whether control variables are included, the regression coefficients of the core explanatory variable, data element configuration level, are significantly positive at least at the 5% level. indicating that the development of data elements in China during the sample period significantly promoted the modernization of the industrial chain, thereby validating the robustness of the conclusions.

Table 3. Robustness test: measured using one period lagged data

	Ind	Ind
L.data	0.368***	0.320*
	(0.093)	(0.101)
control variable	uncontrolled	containment
province effect	containment	containment
time effect	containment	containment
sample size	300	300
R2	0.905	0.932

The above estimation results are all based on static panel regression models. When the modernization level of the industrial chain exhibits path dependence, the robustness of the research conclusions may be affected. To address this, this paper introduces the first-order lagged terms of the explained variables into the model and constructs a dynamic panel model for re-estimation. Table 4 reports the results of the difference GMM estimation in Column (1) and the system GMM estimation in Column (2). After controlling for the dynamic effects of the model, the estimated coefficients for the level of data element allocation remain significant.

Table 4. Robustness tests: Using dynamic panel estimation

variant	differential GMM	System GMM
Data	1.156** (0.483)	0.728*** (0.237)
control variable	containment	containment
sample size	270	300
AR2	0.525	0.660
Hansen	0.784	0.919

Note: AR(2) and Hansen values are p-values for tests.

5.4 Mediating Effect

Theoretical analysis indicates that improving the level of data element allocation can help to further enhance the rational allocation of resources and advance the modernization of the industrial chain. To verify this mechanism, this paper sets up the following mediation effect model for testing. The benchmark regression results show (Tables (2) and (4)) that the level of data element allocation has a significant negative impact on both the capital misallocation index and the labor misallocation index (coefficients are significant at the 5% level). This indicates that improving the level of data element allocation can effectively promote the rational allocation of elements across industries.

$$taul_{it} = \beta_0 + \beta_1 \mathrm{data}_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$\mathrm{ind}_{it} = \gamma_0 + \gamma_1 \mathrm{data}_{it} + \gamma_2 tauL_{it} + \gamma_3 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

$$tauk_{it} = \beta_0 + \beta_1 \mathrm{data}_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

$$\mathrm{ind}_{it} = \gamma_0 + \gamma_1 \mathrm{data}_{it} + \gamma_2 tauk_{it} + \gamma_3 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

Column (1) includes the intermediate variable of labor mismatch index. The coefficients of data element mismatch level on labor mismatch index and labor mismatch index on industrial chain modernization level are both significantly negative. Additionally, the absolute values of the coefficients of data element allocation level are smaller compared to the baseline regression table, indicating that reducing the labor mismatch index is the mechanism through which data element mismatch level improves industrial chain modernization level. Column (3) includes the capital mismatch index. Although the capital mismatch index is positively correlated with the level of industrial chain modernization, this does not mean that capital mismatch is a good phenomenon. The positive and significant impact of the capital mismatch index on the level of industrial chain modernization may be due to the fact that, during the process of industrial chain modernization, old capital may be replaced by new, more efficient capital. This replacement may lead to capital mismatch because the old capital may not have been fully depreciated, while the new capital has already been put into use. The capital misallocation index involves multiple factors, including the quantity, structure, and flow of capital. These factors may offset or intertwine with each other during the modernization of industrial chains, making the relationship between the capital misallocation index and the level of industrial chain modernization less evident. Therefore, in pursuing industrial chain modernization, efforts should be made to minimize capital misallocation and ensure that capital is effectively allocated and utilized.

Table 5. Regression results of the mediating effect of factor allocation levels

	(1)	(2)	(3)	(4)
	Ind	taul	Ind	tauk
taul	-0.029**			
	(0.011)			
tauk			0.029***	

			(0.009)	
data	0.331***	-0.344**	0.357***	-0.573***
	(0.023)	(0.128)	(0.023)	(0.154)
control variable	containment	containment	containment	containment
province effect	containment	containment	containment	containment
time effect	containment	containment	containment	containment
sample size	330	330	330	330
R2	0.951	0.200	0.952	0.554

5.5 Heterogeneity Analysis

Since the reform and opening-up, China's economy has developed rapidly, but there are significant differences in economic conditions and resource endowments across regions. Therefore, it is necessary to analyze the regional heterogeneity of the impact of data element allocation levels on industrial chain modernization.

Based on the results of the heterogeneity analysis, it can be observed that the regression coefficient for the eastern region is the highest and statistically significant at the 1% level, while the regression coefficients for the western and central regions are relatively lower and less significant. This indicates that in the eastern region, the level of data element allocation has the most significant impact on promoting industrial chain modernization. The opposite is true for the western and central regions. This is closely related to the current development status and strength of the digital economy in the three major regions. Overall, China's regional data trading platforms exhibit a pattern of stronger performance in the east and weaker performance in the west. According to data from the “2023 China Data Trading Market Research and Analysis Report,” China's economic zones with significant data trading markets are primarily concentrated in the Yangtze River Economic Belt, particularly in the Yangtze River Delta region, including Shanghai, Anhui, Zhejiang, and Jiangsu. These regions account for 26.8% of the national data trading market. Additionally, the internet industry in the eastern regions has also demonstrated significant growth momentum. Benefiting from the technological and hardware/software foundations established by internet companies for the data trading market, the eastern regions' data trading market has developed earlier and possesses a solid foundation in multiple aspects.

Table 6. Sub-regional estimates

	East	Middle	West
data	0.362***	0.002	0.056
	(0.040)	(0.105)	(0.080)
control variable	containment	containment	containment
province effect	containment	containment	containment
time effect	containment	containment	containment
sample size	121	110	99
R2	0.960	0.962	0.979

5.6 Spatial Spillover Effect Analysis

In the study of spatial spillover effects, this paper employs the global Moran's I index to measure the spatial autocorrelation of data element allocation levels across provinces under two different spatial weight matrices from 2011 to 2021. Empirical results show that the Moran's I indices for both matrices are positive, and their p-values are both below 0.001. This indicates that during the 2011–2021 period, the allocation of data elements across provinces in China exhibited strong spatial correlation. Next, we tested whether the spatial Durbin model could be reduced to a spatial error model or a spatial lag model. Both the LR and WALD tests rejected the null hypothesis at the 1% significance level. Under both weighting matrices, the direct effect of data element allocation levels on industrial chain modernization levels was significantly positive at the 1% level, This indicates that the level of data element allocation can promote the improvement of local ecological efficiency and has a significant positive indirect effect on the efficient production processes of enterprises at the 5% level. This suggests that the development of local data element allocation levels can stimulate the modernization of industrial chains in neighboring provinces, thereby enhancing their modernization levels, which is crucial for improving production efficiency and efficiency across all stages.

Table 7. Analysis of spatial spillover effects

variant	Geographic distance weighting matrix w1			Nested weight matrix of economic-geographical distances w2		
	direct effect	indirect effect	aggregate	direct effect	indirect effect	aggregate
Data	0.365*** (0.027)	0.121** (0.097)	0.486*** (0.103)	0.023*** (0.073)	0.211*** (0.066)	0.134*** (0,061)
control variable	containment	containment	containment	containment	containment	containment
province effect	containment	containment	containment	containment	containment	containment
time effect	containment	containment	containment	containment	containment	containment
lgL	992.209	992.209	992.209	967.854	967.854	967.854
N	330	330	330	330	330	330
R2	0.064	0.064	0.064	0.058	0.058	0.058

6. Research Conclusions and Policy Recommendations

Based on a systematic discussion of the relationship between data elements and industrial chain modernization, this paper empirically examines the mechanism through which data elements influence industrial chain modernization using panel data from 30 provinces in China from 2011 to 2021. The results indicate: (1) Data elements have a significant positive impact on the level of industrial chain modernization. This conclusion remains valid even after addressing endogeneity issues and using dynamic panel estimation; (2) Data elements can enhance the level of industrial chain modernization by suppressing the labor mismatch index; (3) The effect of data elements on enhancing the level of industrial chain modernization exhibits significant regional heterogeneity: they significantly promote modernization in eastern regions but do not reach statistical significance in central and western regions.

Based on the research findings, the following policy recommendations are proposed:

The empirical results of this study indicate that the impact of data elements on industrial chain modernization exhibits regional heterogeneity. Eastern regions should leverage their abundant data resources, favorable policy environment, and robust urban digital infrastructure to promote the development of data production and circulation sectors. Meanwhile, underdeveloped regions should accelerate the development of data element markets, strengthen data collection and integration, break down information silos, and facilitate the circulation and utilization of data resources. Local governments should also strengthen policy support and guidance, draw on advanced experiences and technologies, and promote the rapid development of data elements in underdeveloped regions.

Based on empirical research findings, while the development of data elements is of significant importance to economic growth and social progress, it may also lead to an increase in capital misallocation. In response, governments and relevant departments should strengthen regulation of the data market, prevent excessive concentration and monopolization of data resources, and promote the fair distribution and rational utilization of data resources. Additionally, we need to enhance the integration of data elements with other elements. The development of data elements should not be conducted in isolation but should be integrated with other elements such as labor, land, and technology to create synergistic effects. By promoting the deep integration of data elements with other elements, we can achieve optimal resource allocation and efficient utilization, thereby reducing the likelihood of capital misallocation.

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