

# Data Factor Empowers New Quality Productive Forces: Evidence from China

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## Abstract

In recent years, with its powerful enabling effect, data factor has become a crucial engine for generating and fostering new quality productive forces. Based on constructing a theoretical framework for how data factor empowers new quality productive forces, this paper utilizes provincial panel data of China from 2011 to 2023, and employs bidirectional fixed-effects and mediating-effect panel models to empirically examine the impact mechanism of data factor on new quality productive forces. The results indicate that data factor significantly and robustly promotes new quality productive forces. Heterogeneity analysis reveals that the driving effect of data factor exhibits notable spatial gradient differences and is more pronounced in regions with a relatively strong foundation in data factor or new quality productive forces, reflecting a self-reinforcing characteristic of “the strong getting stronger”. Mechanism tests demonstrate that data factor can indirectly empower the development of new quality productive forces through two pathways: promoting industry-university-research collaboration and optimizing industrial structure. This study contributes to deepening the understanding of the internal logic of how data factor empowers new quality productive forces, and provides references for relevant policy formulation to better unleash the value of data factor and systematically enhance the development of new quality productive forces.

## Keywords

Data Factor, New Quality Productive Forces, Industry-University-Research Cooperation, Industrial Structure Optimization

## 1. Introduction

In recent years, with the accelerated evolution of the global scientific and technological revolution and industrial transformation, intensified international compe-

tition, and continuous economic upgrading, the traditional productive forces model has found it difficult to meet the requirements of high-quality development. In September 2023, Chinese President Jinping Xi first proposed the brand-new concept of “new quality productive forces” in response to the development of the times. This not only represents an innovative development of Marxist productive forces theory (Jiang, 2025), but also provides strategic guidance for China to seize the opportunities presented by the scientific and technological revolution and build a modern economic system. New quality productive forces are an advanced form of productive forces where innovation plays a leading role, breaking away from traditional economic growth patterns and productive forces development paths. They are characterized by high technology, high efficiency, and high quality, aligning with the new development philosophy. They are generated by revolutionary technological breakthroughs, innovative allocation of production factors, and in-depth industrial transformation and upgrading. From a structural perspective, new quality productive forces are manifested as an overall leap in the optimization and combination of laborers, means of labor, and objects of labor, with a significant increase in total factor productivity serving as the core indicator (Liu, 2024). This thus provides a clear theoretical basis for a comprehensive measurement built upon laborers, means of labor, and objects of labor. Against the backdrop of the in-depth development of the global digital economy, the data factor possesses more explicit factor attributes compared to the broader concept of the digital economy. The digital economy emphasizes the digital transformation of overall economic activities, whereas the data factor, as a new type of productive factor that is measurable, configurable, and reusable, directly participates in the process of value creation. Particularly important is the non-depreciable nature of the data factor, which enables it to continuously iterate and generate new value through circulation, sharing, and integrated applications. This characteristic allows it to break through the marginal constraints of traditional factors, forming a powerful productive force driving efficiency and innovation spillover effects, thereby becoming a core force driving the development of new quality productive forces and profound changes in the industrial system (Feng & Lin, 2024).

From perspectives such as digital transformation (Zhang & Zhu, 2024; Czarnitzki et al., 2023; Du & Jiang, 2022), digital finance development (Zhu & Zeng, 2024), and the integration of the digital and real economies (Wu & Du, 2024), existing literature has explored the impact of digital economy-related factors on enhancing new quality productive forces. However, there is relatively little academic research directly based on the perspective of data factor empowering new quality productive forces, and the existing studies mainly focus on the impact of factors such as the marketization of data factor and data openness on the new quality productive forces of enterprises. The research methods employed primarily include the difference-in-differences (DID) model, mediation mechanism analysis model, machine learning model, text data mining methods and so on. Studies by Lu & Wang (2024), Luo et al. (2025), Yao et al. (2025), etc., regard the establishment of data trading

platforms in China as a quasi-natural experiment. These studies find that the marketization of data factor can significantly enhance the new quality productive forces of enterprises by incentivizing disruptive technological innovation, promoting the deep integration of the digital economy and the real economy, optimizing factor allocation, and reconstructing innovation paradigms. Variables such as industrial upgrading and transformation, digital talent aggregation, and export technology sophistication play effective moderating roles. Studies by Xue (2025), Feng & Lin (2024), etc., find that data factor has given rise to new quality means of production such as artificial intelligence models, as well as a large number of new industries, new business forms, and new models, and has cultivated new quality labor forces that meet the needs of the digital economy development era. Studies by Zhong et al. (2025), etc., show that public data openness can drive a leap in the new quality productive forces of enterprises by improving the quality of information disclosure, enhancing innovation quality, and improving supply chain efficiency. Moreover, intellectual property protection, science and technology financial expenditures, and digital transformation play a positive moderating role in the relationship between public data openness and new quality productive forces. Studies by Wang et al. (2024), etc., argue that data factor can effectively drive enterprises to achieve higher-quality development in green innovation, especially in state-owned enterprises, high-tech enterprises, capital-intensive and technology-intensive enterprises, and enterprises with low financial constraints, where the empowering effect of data factor is more significant.

In summary, among the existing relevant studies, there is still room for further improvement in research on the impact of data factor on the regional disparities and situational heterogeneity of new quality productive forces. On the basis of fully drawing on these research findings, this paper systematically examines the impact effect and internal mechanism of data factor on new quality productive forces based on China's provincial panel data, aiming to provide useful references and insights for subsequent academic research and practical applications. The marginal contributions of this paper are mainly reflected in the following two aspects: First, from the perspective of combining theory and empirical evidence, it systematically analyzes the pathways through which data factor promotes the development of new quality productive forces, expanding the theoretical framework and empirical evidence of research on new quality productive forces in the digital economy era. Second, from the three dimensions of regional disparities, development stages, and transmission mechanisms, it deeply reveals the heterogeneous characteristics and multi-channel mechanisms of the impact of data factor on the development of new quality productive forces, providing new empirical evidence for understanding its differentiated effects and also offering decision-making references for various regions to implement precise policies and promote coordinated regional development.

The arrangement of the remaining part of this article is as follows. The second part will establish a theoretical analysis framework for how data factor empowers

new quality productive forces and put forward research hypotheses. The third part, concerning research design, mainly introduces the intended research methods, models, indicators, and data. The fourth part is the empirical analysis section, which takes China's provincial panel data as an example to conduct a detailed analysis of the paths and mechanisms through which data factor drives the development of new quality productive forces. The fifth part presents the conclusions and policy recommendations.

## **2. Theoretical Analysis and Research Hypotheses**

Data factor can drive the development of new quality productive forces not only through direct paths but also through indirect paths such as promoting industry-university-research collaboration and optimizing industrial structure.

### **2.1. The Direct Impact Effect of Data Factor Empowering the Development of New Quality Productive Forces**

Against the backdrop of the rapid development of the digital economy, actively developing new means of production centered around algorithms and computing power and fully leveraging the multiplier effect of data factor have become key drivers for promoting the development of new quality productive forces. Data factor serves not only as an important means of production but also as a core variable leading innovative development. By relying on data factor to drive the innovation and application of general-purpose technologies, it can effectively empower traditional factors of production and enhance their allocation efficiency and value-creation capabilities.

#### **2.1.1. At the Level of Laborers**

Data factor has a profound impact on the labor factor in new quality productive forces by enhancing the digital literacy and innovation capabilities of laborers. The application of data factor prompts laborers to transition from traditional production modes to intelligent and digital production modes, improving their production efficiency and skill levels. For example, in the manufacturing industry, laborers optimize production processes through data analysis, enabling precise operations and significantly enhancing production efficiency and product quality (Xu et al., 2024). Meanwhile, data factor has also given rise to new occupational types, such as data analysts and data scientists. These new types of laborers possess higher digital skills and innovation capabilities, becoming important forces driving the development of new quality productive forces (Jiang & Liu, 2025).

#### **2.1.2. At the Level of Objects of Labor**

Data factor expands the scope and forms of objects of labor, enabling non-material data to become new objects of labor. The widespread application of data factor prompts enterprises to transition from traditional material production to data-driven service-oriented manufacturing, with data becoming an important resource for enterprises to create value. For instance, in the service industry, enter-

prises provide personalized services by analyzing user behavior data, achieving a transition from product production to service provision and enhancing user experience and satisfaction (Zhang & Li, 2024). Additionally, data factor has also driven the emergence of new industries and business formats, such as the big data industry and the artificial intelligence industry. These emerging industries take data as their core production factor and create new economic growth points through data analysis and mining (Xu et al., 2025).

### 2.1.3. At the Level of Means of Labor

As a new type of means of production, data factor has facilitated the intelligent upgrading and digital transformation of means of labor. The introduction of data factor enables traditional means of labor, such as machinery and equipment and production lines, to undergo intelligent transformation, improving production automation levels and production efficiency. For example, through the Internet of Things technology, production equipment can achieve interconnection and real-time monitoring. The flow of data factor enables equipment to self-optimize and adjust based on real-time data, significantly enhancing production efficiency and flexibility. Furthermore, data factor has also promoted the emergence of new means of labor, such as intelligent robots and 3D printing equipment, which further elevate the intelligent and flexible levels of the production process (Zhou & Xu, 2023). Based on the above analysis, this article proposes the following hypothesis:

**H1:** Data factor has a positive driving effect on the enhancement of new quality productive forces.

## 2.2. The Indirect Impact Effect of Data Factor Empowering the Development of New Quality Productive Forces

Among the impact paths of data factor on new quality productive forces, industry-university-research collaboration, as a crucial intermediary mechanism, significantly amplifies the empowering effect of data factor. Specifically, by driving the deep integration of industry, universities, and research institutions, data factor constructs a conversion chain of “data - knowledge - technology - industry”: Universities and research institutions can precisely identify industrial technological needs, optimize research directions and resource allocation, and form a demand-oriented research and development model by relying on the sharing and analysis capabilities of data factor (Jiang & Liu, 2025). Enterprises, through industry-university-research collaboration platforms, can rapidly transform scientific research achievements driven by data factor into practical productive forces such as production process optimization and product iteration (Zhang & Li, 2024). In addition, the cross-entity flow of data factor also promotes the collaborative evolution of the innovation ecosystem. Universities provide support for basic research, research institutions drive technological integration, and enterprises lead market applications. The three form a closed loop of “demand traction - technological breakthrough - commercial verification” through data-sharing mechanisms, accelerating the incubation of disruptive technologies in new quality productive forces (Xu et al., 2024).

In summary, by strengthening the paths of knowledge sharing, scientific research collaboration, and achievement transformation among industry, universities, and research institutions, data factor effectively improves the efficiency and quality of innovation activities, making industry-university-research collaboration the core intermediary mechanism for data factor to empower the development of new quality productive forces. Based on this, the following hypothesis is proposed:

**H2:** Data factor can exert a significant driving effect on the development of new quality productive forces through the key path of promoting industry-university-research cooperation.

In the process of data factor promoting the development of new quality productive forces, industrial structure optimization plays a crucial intermediary role. After reaching a certain scale in practical applications, data factor has differentiated scale return effects on different industries due to its non-rivalry and positive externalities, thereby changing the allocation of factors and output structure among industries and driving the transformation of the industrial structure towards high efficiency and high added value (Guo et al., 2024). At the same time, by integrating with traditional factors such as labor, capital, and technology, data factor promotes industrial integration and the improvement of total factor productivity, forming new quality means of labor, objects of labor, and laborers. This process can be realized through the evolutionary chain of industrial structure: “resourceization - assetization - capitalization”, thereby facilitating the development of new quality productive forces (Jiang & Liu, 2025). From the perspective of changes in factor endowments in production, data factor not only participates in social production as a direct input factor but also drives profound changes in the industrial structure through two theoretical mechanisms: driving innovation and promoting the deepening of social division of labor. Innovation driving is manifested in data factor promoting knowledge accumulation and creative renewal, while the deepening of division of labor is manifested in data factor reconstructing the allocation mode of traditional production factors and driving the evolution of industrial organization models towards networking and platformization (Wang, 2024). Therefore, industrial structure optimization is not only an intermediary mechanism for data factor to empower new quality productive forces but also a core carrier for its structural leap, providing key nodes for policy guidance and market allocation. Based on this, the following hypothesis is proposed:

**H3:** Data factor can exert a significant driving effect on the development of new quality productive forces through the key path of industrial structure optimization.

### 3. Research Design

#### 3.1. Model Construction

This paper empirically tests the impact of data factor on new quality productive forces by constructing a benchmark regression model as shown in Equation (1), aiming to deeply reveal the transmission path and internal mechanism through which data factor acts on new quality productive forces.

$$NQP_{it} = \alpha_0 + \alpha_1 DAT_{it} + \alpha_2' C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where,  $i$  and  $t$  represent province and year, respectively;  $NQP_{it}$  denotes the development of new quality productive forces;  $DAT_{it}$  is the core independent variable, representing the development of data factor;  $C_{it}$  is a series of control variables;  $\alpha_0$ ,  $\alpha_1$ , and  $\alpha_2$  are the parameters to be estimated in the model;  $\mu_i$  and  $\lambda_t$  represent province and time fixed effect, respectively; and  $\varepsilon_{it}$  is the random disturbance term.

To verify the mediating roles of two mechanism variables, namely, industry-university-research collaboration and industrial structure optimization, models as shown in Equations (2) and (3) are constructed to test the mediating effects of these variables (Jiang, 2022).

$$M_{it} = \beta_0 + \beta_1 DAT_{it} + \beta_2' C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$NQP_{it} = \gamma_0 + \gamma_1 M_{it} + \gamma_2' C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where,  $M_{it}$  represents the mediating variable, which includes industry-university-research collaboration (UIR) and industrial structure optimization (STR) respectively. To characterize the level of industry-university-research cooperation, this paper measures it using the ratio of R&D expenditure of industrial enterprises above the designated size in each province to the total R&D expenditure (Ren et al., 2024). For measuring industrial structure optimization, this paper adopts the method used by Gan et al. (2011) and constructs a composite indicator based on the labor productivity and value-added share of each industry. The specific formula is shown in Equation (4):

$$STR_{it} = \sum_{j=1}^j G_{ijt} \times L_{ijt} \quad (4)$$

where,  $j$  represents the primary, secondary, and tertiary industries;  $G_{ijt}$  denotes the proportion of the value-added of the  $j$ -th industry in region  $i$  in year  $t$  to the regional GDP;  $L_{ijt}$  represents the labor productivity of employees in the  $j$ -th industry in region  $i$  in year  $t$ , that is, the ratio of the value-added of each industry to the total employment of that industry. The meanings of the remaining variables in Equations (2) and (3) are the same as those in Equation (1).

## 3.2. Variable Explanation

### 3.2.1. Dependent Variable: Development of New Quality Productive Forces (NQP)

According to the connotation of new quality productive forces, the formation and development of new quality productive forces are essentially a systematic evolutionary process in which the three basic elements—laborers, means of labor, and objects of labor—work together in a coordinated and dynamically adaptive manner to achieve overall efficiency optimization (Jiang & Liu, 2025). At the level of laborers, the foundation for their empowerment lies in the human capital reserve represented by the quality of laborers. Their effectiveness is reflected in the value creation efficiency indicated by labor productivity, and their

development orientation is determined by the innovative and proactive spirit measured by laborer awareness (Wang & Wang, 2024). At the level of objects of labor, the focus is on two aspects: industrial development and ecological environment. Among them, emerging industries and future industries represent the advancement of the industrial structure, while green environmental protection and pollution reduction depict the sustainability of its development (Zhou & Xu, 2023). At the level of means of labor, their material foundation conditions

**Table 1.** Indicator system for the development of new quality productive forces.

| Target layer                                 | Criterion layer  | Primary indicator         | Secondary indicator                                  | Tertiary indicator   |  |
|--|------------------|---------------------------|--|--|--|
| Development of new quality productive forces | Laborers         | Laborer quality           | Education  | Average years of education per capita                                |  |
|  |                  |                           | Human capital structure                              | Proportion of college students in total population                   |  |
|  |                  | Labor productivity        | Per capita output value                              | GDP/Total population   |  |
|  |                  |                           | Per capita income                                    | Average wage of on-the-job employees                                 |  |
|  |                  | Laborer awareness         | Employment philosophy                                | Proportion of employees in the tertiary industry in total employment |  |
|  |                  |                           | Entrepreneurial philosophy                           | Number of newly established enterprises per 100 people               |  |
|  | Objects of labor | Industrial development    | Emerging industries                                  | Proportion of e-commerce enterprises in total enterprises            |  |
|  |                  |                           | Future industries                                    | Revenue from software business and IT services/GDP                   |  |
|  |                  | Ecological environment    | Environmental protection                             | Forest coverage rate   | Environmental protection expenditure/Government public finance expenditure |
|  |                  |                           |  | Pollution reduction  | General industrial solid waste generation/GDP                              |
|  |                  |                           | Investment completed in industrial pollution control |  |  |
|  |                  |                           |  |  |  |
|  | Means of labor   | Physical means of labor   | Infrastructure                                       | Highway mileage  |  |
|  |                  |                           |  | Railway mileage  |  |
|  |                  |                           |  | Optical cable density  |  |
|  |                  | Intangible means of labor | Energy consumption                                   | Energy consumption/GDP   |  |
|  |                  |                           |  | Total electricity consumption/Total energy Consumption               |  |
|  |                  |                           | Scientific and technological innovation              | Number of patent grants/Total population                             |  |
|  | Digitalization   | R&D expenditure/GDP       |  |  |  |
|  |                  | Digital Economy Index     |  |  |  |
| Enterprise digitalization                    |                  |                           |  |  |  |

and green input efficiency as part of the production process are measured through infrastructure and energy consumption. Meanwhile, their core role as carriers of technological progress and intelligent empowerment is evaluated through the level of scientific and technological innovation and the level of digitalization (Zhang et al., 2024). Here, referring to relevant research results, an indicator system is constructed as shown in **Table 1** to comprehensively measure the development of new quality productive forces, and the entropy-weighted TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method is used for calculation.

### 3.2.2. Independent Variable: Development of Data Factor (DAT)

To overcome the difficulties in directly quantifying the data factor due to its implicit characteristics and dependence on external environments, this study adopts the analytical framework proposed by He & Yan (2025) to construct an indicator system for assessing the development of the data factor from three dimensions: foundational support, application, and transformation efficiency (see **Table 2** for details). This system measures, respectively, the completeness of data infrastructure, the depth of data application in industrial and economic activities, and the capacity to transform data into economic and technological value. By covering the entire chain of the data factor's "generation - application - value release", this indicator system can comprehensively reflect the overall status of regional data factor development. The entropy-weighted TOPSIS method is then employed for the calculation.

**Table 2.** Indicator system for the development of data factor.

| Target index               | Primary indicator                        | Secondary indicator   |
|----------------------------|--|---|
| Development of data factor | Foundational support of data factor      | Number of broadband access ports                              |
|                            |  | Number of internet domain names                               |
|                            |  | Number of internet web pages                                  |
|                            |  | Number of IPV4 addresses                                      |
|                            | Application of data factor               | Number of websites per 100 enterprises                        |
|                            |  | Installation density of industrial robots                     |
|                            |  | Proportion of e-commerce sales in GDP                         |
|                            |  | Proportion of enterprises with e-commerce activities          |
|                            | Transformation efficiency of data factor | Digital inclusive finance-Digital payments                    |
|                            |  | Digital inclusive finance-Digital insurance                   |
|                            |  | Digital inclusive finance-Degree of digitization              |
|                            |  | Sales revenue from new products in high-tech industries ratio |
|                            |  | Software product revenue ratio                                |
|                            |  | Information technology service revenue ratio                  |
|                            |  | Technology market turnover ratio                              |

### 3.2.3. Control Variables

Drawing on the research findings of existing relevant literature and considering the multi-dimensional characteristics exhibited in the development of new quality productive forces, in addition to the independent variable, this study selects a series of control variables to control for the influence of other potential factors (Zhang & Zhu, 2024). 1) Industrialization (IND), measured by the ratio of industrial added value to regional gross domestic product; 2) Degree of government intervention (GOV), assessed using the ratio of government fiscal expenditure to regional gross domestic product; 3) Urbanization (URB), represented by the proportion of urban population in the total population; 4) Informatization (INF), measured by the ratio of the total volume of telecommunication services to regional gross domestic product; 5) Financial development (FIN), indicated by the ratio of the added value of the financial industry at the end of the year to regional gross domestic product.

### 3.3. Data Description and Descriptive Analysis

The data used in this paper consists of panel data from 30 provinces in China spanning from 2011 to 2023 (due to data availability, the sample excludes Tibet, Hong Kong, Macau, and Taiwan regions of China). Data on the development of new quality productive forces, the development of data factor, and control variables are sourced from the *China Statistical Yearbook*, *China Statistical Yearbook on Science and Technology*, *China Population and Employment Statistical Yearbook*, as well as statistical yearbooks of various provinces, statistical bulletins on national economic and social development of various provinces, and Mark Database (<https://www.macrodats.cn/>). Missing values are filled in using the linear interpolation method. Based on the regional classification standards of National Bureau of Statistics of China, this paper divides China's 30 provinces into four major regions (eastern, central, western, and northeastern) for analysis.

**Table 3.** Descriptive statistics of variables.

| Variable category    | Variable | Total (N = 390) | Eastern region (N = 130) | Central region (N = 78) | Western region (N = 143) | Northeastern region (N = 39) | Standard deviation | Maximum | Minimum |
|----------------------|----------|-----------------|--------------------------|-------------------------|--------------------------|------------------------------|--------------------|---------|---------|
| Dependent variable   | NQP      | 0.153           | 0.196                    | 0.127                   | 0.137                    | 0.123                        | 0.073              | 0.607   | 0.072   |
| Independent variable | DAT      | 0.129           | 0.211                    | 0.101                   | 0.079                    | 0.091                        | 0.104              | 0.675   | 0.017   |
| Mediating variables  | IUR      | 0.660           | 0.650                    | 0.763                   | 0.631                    | 0.595                        | 0.173              | 0.905   | 0.119   |
|                      | STR      | 14.165          | 17.636                   | 12.117                  | 12.679                   | 12.139                       | 6.186              | 39.497  | 4.449   |
| Control variables    | IND      | 0.331           | 0.321                    | 0.376                   | 0.319                    | 0.322                        | 0.080              | 0.574   | 0.100   |
|                      | GOV      | 0.257           | 0.188                    | 0.209                   | 0.337                    | 0.295                        | 0.111              | 0.758   | 0.105   |
|                      | URB      | 0.606           | 0.705                    | 0.550                   | 0.539                    | 0.637                        | 0.120              | 0.896   | 0.350   |
|                      | INF      | 0.048           | 0.039                    | 0.041                   | 0.061                    | 0.049                        | 0.050              | 0.285   | 0.010   |
|                      | FIN      | 0.073           | 0.093                    | 0.052                   | 0.068                    | 0.068                        | 0.032              | 0.198   | 0.026   |

According to the descriptive statistics in **Table 3**, the development of new quality productive forces and the development of data factor exhibit distinct regional imbalances. From the perspective of the national sample, both the development of new quality productive forces and the development of data factor in the eastern region significantly outperform those in other regions, indicating that the eastern region takes the lead in cultivating new quality productive forces and the data factor. In contrast, the development of new quality productive forces and the development of data factor in the central, western, and northeastern regions are all lower than the national average, revealing significant developmental gradient differences. Meanwhile, other control variables also show systematic differences across regions, providing a necessary regional comparison basis for subsequent empirical analysis.

## 4. Empirical Analysis

### 4.1. Analysis of Benchmark Regression Results

To examine the impact of data factor development on new quality productive forces, this paper employs a two-way fixed-effects model, which can simultaneously control for the inherent characteristics of each province that do not change over time and the time-trend shocks experienced by all regions collectively. This approach enables a more accurate identification of the net effect of core variables by eliminating interference from unobservable heterogeneity, thereby reducing estimation bias caused by the omission of key contextual factors. As shown in **Table 4**, the model presented in Column (1) does not control for time and province fixed effect and does not include control variables. The coefficient for the development of data factor is 0.529, which is significant at the 1% level, initially confirming a positive correlation between it and the development of new quality productive forces. After introducing two-way fixed effects in the model shown in Column (2), the coefficient rises to 0.855, with no change in significance, demonstrating strong robustness. Further, after incorporating control variables into the model shown in Column (3), the regression coefficient for the development of data factor remains significantly positive, indicating its stable promoting effect in enhancing new quality productive forces. This thereby validates the research hypothesis H1 proposed in this paper.

### 4.2. Endogeneity and Robustness Tests

To ensure the reliability of the benchmark regression conclusions, this paper conducts a series of tests targeting potential endogeneity issues and estimation robustness.

#### 4.2.1. Endogeneity Test

To alleviate the endogeneity issue in the development of the data factor, this study selects the number of fixed-line telephones in 1984 as an instrumental variable (Zhao et al., 2020). Its validity is primarily demonstrated in two aspects: First,

**Table 4.** Benchmark regression results.

| Variable       | (1)<br>NQP          | (2)<br>NQP          | (3)<br>NQP           |
|----------------|---------------------|---------------------|----------------------|
| DAT            | 0.529***<br>(0.048) | 0.926***<br>(0.121) | 0.785***<br>(0.117)  |
| IND            |                     |                     | -0.305***<br>(0.078) |
| GOV            |                     |                     | 0.090<br>(0.067)     |
| URB            |                     |                     | -0.740***<br>(0.107) |
| INF            |                     |                     | 0.153**<br>(0.068)   |
| FIN            |                     |                     | -0.217<br>(0.258)    |
| _cons          | 0.085***<br>(0.005) | 0.034**<br>(0.015)  | 0.588***<br>(0.093)  |
| Time fixed     | No                  | Yes                 | Yes                  |
| Province fixed | No                  | Yes                 | Yes                  |
| R <sup>2</sup> | 0.565               | 0.791               | 0.824                |
| Observations   | 390                 | 390                 | 390                  |

Note: \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively. Values in parentheses are standard errors. The same applies below.

communication infrastructure from historical periods forms the early material foundation for regional informatization development, maintaining a correlation with the current development of the data factor through a path-dependency mechanism. Second, the communication in 1984 mainly reflects the infrastructure construction pattern at that time, showing minimal association with current factors influencing new quality productive forces, such as institutional environments, industrial structures, and innovation capabilities. It is thus unlikely to directly affect the present new quality productive forces, thereby adequately satisfying the exclusivity restriction. Since the data for this variable is cross-sectional and cannot be directly used in a panel model, it is multiplied by the number of internet users in the previous year to construct an instrumental variable with a temporal dimension. To test the robustness of the results, this study also employs the first-order lag of the development of the data factor as another instrumental variable (Xia et al., 2023). In terms of regression methodology, the two-stage least squares (2SLS) method is adopted for analysis. The results are presented in Table 5. The results in Columns (1) and (3) both indicate a significant correlation between the instrumental variables and the dependent variable. Moreover, both the Kleibergen-Paap LM test and the Cragg-Donald Wald F test significantly reject the null hypothesis, demonstrating that the selection of instrumental variables is reasona-

ble and effective. Based on this, the results in Columns (2) and (4) show that the impact of the development of the data factor on the development of new quality productive forces remains significantly positive at the 1% level, indicating that the core conclusion of the benchmark regression model still holds after controlling for endogeneity issues.

**Table 5.** Test results (2SLS).

| Variable  | (1)                  | (2)                  | (3)                  | (4)                  |
|---|----------------------|----------------------|----------------------|----------------------|
|   | DAT                  | NQP                  | NQP                  | NQP                  |
| DAT   |                      | 1.025***<br>(0.120)  |                      | 0.674***<br>(0.083)  |
| IV1   | 0.138***<br>(0.024)  |                      |                      |                      |
| IV2   |                      |                      | 1.023***<br>(0.015)  |                      |
| _cons   | 0.030<br>(0.032)     | -0.079***<br>(0.023) | 0.010<br>(0.007)     | -0.065***<br>(0.021) |
| Under-identification test (Kleibergen-Paapr LM)     | 35.590***<br>{0.000} |                      | 50.123***<br>{0.000} |                      |
| Weak identification test (Cragg-Donald Weak Wald F) | 30.676<br>[16.38]    |                      | 5570.113<br>[16.38]  |                      |
| Control variables                                   | Yes                  | Yes                  | Yes                  | Yes                  |
| Time fixed  | Yes                  | Yes                  | Yes                  | Yes                  |
| Province fixed                                      | Yes                  | Yes                  | Yes                  | Yes                  |
| R <sup>2</sup>                                      | 0.674                | 0.548                | 0.979                | 0.645                |
| Observations  | 390                  | 390                  | 360                  | 360                  |

**Table 6.** Robustness test results.

| Method            | (1)                                      | (2)                       | (3)                              | (4)                       | (5)                        |
|-------------------|--|---------------------------|----------------------------------|---------------------------|----------------------------|
|                   | Second-order lag of independent variable | Adjusting the sample size | Replace the independent variable | Replace control variables | Adjusting the sample scope |
| Variable          | NQP                                      | NQP                       | NQP                              | NQP                       | NQP                        |
| DAT               |  | 0.785***<br>(0.130)       | 0.087***<br>(0.009)              | 0.793***<br>(0.136)       | 1.053***<br>(0.167)        |
| L2.DAT            | 0.787***<br>(0.139)                      |                           |                                  |                           |                            |
| _cons             | 0.620***<br>(0.120)                      | 0.588***<br>(0.097)       | 0.390***<br>(0.085)              | 0.567**<br>(0.104)        | 0.698***<br>(0.124)        |
| Control variables | Yes                                      | Yes                       | Yes                              | Yes                       | Yes                        |
| Time fixed        | Yes                                      | Yes                       | Yes                              | Yes                       | Yes                        |
| Province fixed    | Yes                                      | Yes                       | Yes                              | Yes                       | Yes                        |
| R <sup>2</sup>    | 0.836                                    | 0.824                     | 0.866                            | 0.825                     | 0.803                      |
| Observations      | 330                                      | 390                       | 390                              | 360                       | 338                        |

#### 4.2.2. Time Lag Test

To further examine the credibility of the benchmark regression results, this paper applies a second-order lag to the core independent variable (the development of data factor) to capture the persistence of its impact and reduce concurrent interference. The test results are shown in **Table 6**. The results in Column (1) indicate that after introducing the lagged term, the development of data factor still significantly promotes the development of new quality productive forces, remaining consistent with the benchmark regression conclusion.

#### 4.2.3. Adjusting the Sample Size

Considering that the sample size may affect estimation accuracy, this paper employs the bootstrap method for repeated sampling to enhance the robustness of the inferences. The results in Column (2) of **Table 6** indicate that the estimated coefficient of the development of data factor remains significant in the simulated samples, suggesting that the core conclusion of the benchmark regression is less affected by sample randomness.

#### 4.2.4. Replacing the Independent Variable

To mitigate potential interference from variable measurement methods on the results, this paper re-measures the development of data factor using principal component analysis and conducts regression tests again. The regression results in Column (3) of **Table 6** show that the core conclusion of the benchmark regression still holds, indicating that the conclusion exhibits good robustness to different measurement methods for independent variables.

#### 4.2.5. Replacing Control Variables

To control for the impact of potential omitted factors that evolve over time on the development of new quality productive forces, this paper interacts all control variables in the benchmark model with time trend terms (using 2010 as the base year) to form a new set of control variables for estimation. The regression results in Column (4) of **Table 6** demonstrate that, after considering the temporal heterogeneity of variable impacts, the coefficient for the development of data factor remains significantly positive.

#### 4.2.6. Adjusting the Sample Scope

Finally, to enhance the generalizability of the benchmark regression conclusion, this paper re-estimates the model after excluding samples from municipalities directly under the central government, which may possess unique characteristics. The results in Column (5) of **Table 6** reveal that, after adjusting the sample, the positive impact of development of data factor on the development of new quality productive forces remains robust, indicating that the core conclusion of the benchmark regression exhibits good generality across different sample scopes.

### 4.3. Analysis of Regional Heterogeneity

To thoroughly investigate the regional heterogeneity in the impact of develop-

ment of data factor on the development of new quality productive forces, this paper conducts examinations from three dimensions: the geographical location, the development of data factor, and the foundational level of new quality productive forces itself.

First, from the results of the regional heterogeneity test (see **Table 7**), the coefficients of the data factor across the four major regions are all positive and pass statistical tests at the 10% significance level, indicating that it generally promotes new quality productive forces in all regions, though there are notable gradient differences in the magnitude of its impact. Specifically, a spatial differentiation pattern of “eastern regions leading, central and western regions following, and northeastern regions lagging relatively” is observed. This outcome may stem from accumulated disparities among regions in terms of digital infrastructure, innovation ecosystems, and industrial structures, reflecting that the driving effectiveness of the data factor is constrained by the overall regional development conditions. Therefore, when promoting the empowerment of new quality productive forces by the data factor, it is essential to address interregional development imbalances and implement differentiated support policies.

**Table 7.** Results of geographical location heterogeneity test.

| Variable          | (1)                 | (2)                 | (3)                 | (4)                |
|-------------------|---------------------|---------------------|---------------------|--------------------|
|                   | NQP (eastern)       | NQP (central)       | NQP (western)       | NQP (northeastern) |
| DAT               | 0.707***<br>(0.144) | 0.453***<br>(0.101) | 0.532***<br>(0.111) | 0.275*<br>(0.156)  |
| _cons             | 0.409<br>(0.289)    | 0.346**<br>(0.150)  | 0.511***<br>(0.112) | -0.175<br>(0.201)  |
| Control variables | Yes                 | Yes                 | Yes                 | Yes                |
| Time fixed        | Yes                 | Yes                 | Yes                 | Yes                |
| Province fixed    | Yes                 | Yes                 | Yes                 | Yes                |
| R <sup>2</sup>    | 0.848               | 0.896               | 0.860               | 0.930              |
| Observations      | 130                 | 78                  | 143                 | 39                 |

Secondly, to examine the heterogeneity in the impact of differences in the level of data factor development on the development of new quality productive forces, this study divides the sample into a “high-level data factor development group” and a “low-level data factor development group” based on the data factor development level of each province, using the national average as the dividing standard. Regression tests are then conducted separately to reveal differences in the impact of development of data factor on the development of new quality productive forces at different development stages. From the results shown in Columns (1) and (2) of **Table 8**, regardless of whether it is in the high-level group or the low-level group of the development of data factor, the coefficients of the development of data factor are significantly positive at the 1% statistical level, indicating that the promoting effect of the data factor on new quality productive forces is univer-

sal across groups. However, its impact intensity is notably stronger in the high-level group, suggesting that in regions with a relatively solid foundation in the data factor, the marginal contribution of the data factor is more prominent, potentially exhibiting a self-reinforcing characteristic of “the strong getting stronger”. This result suggests that data infrastructure and data application capabilities may have cumulative and amplifying effects. Therefore, at the policy level, greater investment should be made in data infrastructure and application development in regions with lower levels, enhancing their capacity to bear and transform the data factor, and preventing the further widening of regional disparities during the digitalization process.

**Table 8.** Results of heterogeneity test on development of data factor and new quality productive forces.

| Region            | (1)                                      | (2)                                     | (3)                                  | (4)                                 |
|-------------------|--|---|--------------------------------------|-------------------------------------|
|                   | High-level data factor development group | Low-level data factor development group | High-level economic resilience group | Low-level economic resilience group |
| Variable          | NQP                                      | NQP                                     | NQP                                  | NQP                                 |
| DAT               | 0.735***<br>(0.149)                      | 0.526***<br>(0.079)                     | 0.686***<br>(0.114)                  | 0.468***<br>(0.076)                 |
| Control variables | Yes                                      | Yes                                     | Yes                                  | Yes                                 |
| Time fixed        | Yes                                      | Yes                                     | Yes                                  | Yes                                 |
| Province fixed    | Yes                                      | Yes                                     | Yes                                  | Yes                                 |
| R <sup>2</sup>    | 0.848                                    | 0.826                                   | 0.878                                | 0.800                               |
| Observations      | 130                                      | 260                                     | 130                                  | 260                                 |

Finally, to further analyze the heterogeneous characteristics of the self-level of new quality productive forces within the influencing mechanism of the data factor, this study similarly divides the samples into a “high-level group of new quality productive forces” and a “low-level group of new quality productive forces” based on the varying levels of new quality productive forces across provinces, and conducts separate regressions for each group. From the results shown in Columns (3) and (4) of **Table 8**, the development of data factor also demonstrates significant promoting effects in both the high-level and low-level groups of new quality productive forces, though the coefficient remains higher in the high-level group. This indicates that regions with more advanced development of new quality productive forces exhibit stronger capabilities in applying and transforming the data factor, further confirming the profound impact of regional initial conditions on the enabling effects of the data factor.

Overall, the heterogeneity tests conducted in this section reveal an important phenomenon: the contribution of the data factor depends not only on its own accumulation but also on the overall regional development environment and the capacity to apply the data factor. This finding suggests that policy formulation should emphasize bidirectional synergy, focusing both on continuously strengthening the foundation of the data factor and comprehensively enhancing regional

capabilities to utilize and mine the data factor.

#### 4.4. Test of the Mediating Mechanism

To thoroughly explore the internal mechanism through which the data factor influences new quality productive forces, this paper constructs a mediating effect model and conducts mechanism tests from two dimensions: industry-university-research collaboration (IUR) and industrial structure optimization (STR), with the results presented in **Table 9**. Among them, the results in Columns (1) and (2) confirm the mediating role of industry-university-research collaboration, thereby validating the basic research hypothesis H2 of this paper. Specifically, the data factor can effectively enhance the depth and breadth of industry-university-research collaboration by promoting information sharing and reducing uncertainties in research and development. This deeply integrated industry-university-research collaboration system further accelerates knowledge spillover and the transformation of scientific and technological achievements, thereby effectively empowering new quality productive forces. The results in Columns (3) and (4) reveal the transmission pathway of industrial structure optimization, indicating that the development of data factor can drive the evolution of industrial structures toward higher sophistication and rationalization by optimizing factor allocation efficiency and fostering emerging digital industries. A more resilient and modern industrial system naturally serves as the core foundation and key carrier for the formation and development of new quality productive forces. Consequently, the basic research hypothesis H3 of this paper is validated.

**Table 9.** Results of the mechanism test.

| Variable          | (1)                  | (2)                 | (3)                 | (4)                 |
|-------------------|----------------------|---------------------|---------------------|---------------------|
|                   | IUR                  | NQP                 | STR                 | NQP                 |
| DAT               | 0.516***<br>(0.102)  |                     | 0.693***<br>(0.066) |                     |
| IUR               |                      | 0.088**<br>(0.037)  |                     |                     |
| STR               |                      |                     |                     | 0.355***<br>(0.048) |
| _cons             | -0.623***<br>(0.187) | 0.879***<br>(0.131) | 0.016<br>(0.121)    | 0.754***<br>(0.122) |
| Control variables | Yes                  | Yes                 | Yes                 | Yes                 |
| Time fixed        | Yes                  | Yes                 | Yes                 | Yes                 |
| Province fixed    | Yes                  | Yes                 | Yes                 | Yes                 |
| R <sup>2</sup>    | 0.942                | 0.738               | 0.962               | 0.770               |
| Observations      | 390                  | 390                 | 390                 | 390                 |

Overall, the promotion of new quality productive forces by the data factor is manifested not only through strengthening collaborative innovation mechanisms

among industry, universities, and research institutions but also by guiding the evolution of industrial structures toward high-end and intelligent directions, thereby becoming an important driving force for the formation of new quality productive forces.

## 5. Conclusions and Policy Recommendations

Based on existing research findings and relevant theoretical support, this paper utilizes provincial panel data from 2011 to 2023 to thoroughly explore the mechanism through which data factor empowers new quality productive forces. Although this paper has conducted a systematic empirical analysis based on provincial panel data, it inevitably has certain limitations. The macro-level data at the provincial level exhibits strong aggregation characteristics, which may obscure micro-level heterogeneities at the city, industry, and enterprise levels, thereby limiting the identification of the mechanisms through which the data factor operates at the micro level. Additionally, the construction of indicators and the selection of instrumental variables are constrained by the availability of historical data, making it difficult to capture the multidimensional complexities of data factor allocation and utilization. Future research could further explore micro-level empirical analyses at the city, industry, or enterprise levels to more precisely identify the efficiency of data factor allocation and its specific pathways for enhancing productivity.

The main conclusions of this paper are as follows:

- 1) The data factor is the core driving force behind new quality productive forces. Empirical results demonstrate that investment in the data factor exhibits a robust and stable enhancing effect on new quality productive forces. To ensure the reliability of this inference, this study not only controls for two-way fixed effects of time trends and regional heterogeneity but also incorporates a series of control variables that may influence productivity. After conducting multiple robustness tests, the positive promoting effect remains consistently robust, further indicating that data, as a new type of critical production factor, is playing an irreplaceable foundational and strategic role in technological breakthroughs and innovation in factor allocation.

- 2) There are significant regional and developmental stage differences in the impact of the data factor on new quality productive forces. From a regional perspective, the eastern region exhibits the strongest effect, followed by the central and western regions, with the northeastern region lagging relatively behind, reflecting spatial differentiation characteristics driven by disparities in digital infrastructure and innovation ecosystems. When grouped by the development level of the data factor, it is evident that the marginal effect of the data factor is more pronounced in high-level regions, demonstrating a “stronger getting stronger” characteristic. Analyzing groups categorized by the level of new quality productive forces reveals that regions with a stronger productivity foundation have higher efficiency in utilizing and mining the data factor. Overall, the driving efficacy of the data factor

depends not only on its own investment but also on the regional development foundation and application capabilities, suggesting that policy formulation needs to simultaneously enhance the supply of the data factor and regional carrying capacity to better unleash its promoting effect on new quality productive forces.

3) The data factor indirectly promotes the development of new quality productive forces through multidimensional mechanisms. On one hand, the data factor can strengthen industry-university-research collaboration by improving the information-sharing environment, reducing research and development uncertainties, and enhancing collaborative innovation efficiency, thereby accelerating knowledge diffusion and the transformation of scientific and technological achievements to enhance new quality productive forces. On the other hand, the data factor also drives the evolution of industrial structures toward higher sophistication and rationalization, improves factor allocation efficiency, and fosters emerging digital industries, thereby constructing a more resilient and modern industrial system that provides solid support for the development of new quality productive forces. Overall, the promoting effect of the data factor on new quality productive forces is manifested both in the strengthening of innovative cooperation mechanisms and in the optimization and upgrading of industrial structures, serving as the core driving force behind the generation of new quality productive forces.

Based on the aforementioned conclusions, this paper proposes the following three policy recommendations:

First, strengthen the foundational institutional framework and unified market construction for the data factor market. It is recommended to prioritize the improvement of foundational institutions such as data property rights, circulation and trading, revenue distribution, and security governance, clearly defining the rights, responsibilities, and interests of all participants in the data factor ecosystem. Simultaneously, efforts should be made to dismantle “data silos” and administrative barriers, promoting the establishment of a unified, standardized, and interconnected large-scale market for the data factor. This will facilitate the orderly flow and efficient aggregation of data across regions, industries, and entities, laying a solid institutional and market foundation for the comprehensive empowerment of new quality productive forces by the data factor.

Second, implement differentiated and graduated regional development strategies. Given the significant regional heterogeneity in the driving effect of the data factor, a one-size-fits-all policy approach should be avoided. For regions with a relatively high foundation, such as the eastern regions, policy priorities should shift towards encouraging breakthroughs in cutting-edge technologies and ecosystem construction, supporting their efforts to establish global innovation hubs for the data factor. For the central, western, and northeastern regions, it is essential to precisely address shortcomings in digital infrastructure, strengthen talent introduction and cultivation, and enhance their capacity to absorb and transform the data factor through preferential fiscal and financial policies, thereby forming

a graduated development pattern that aligns with regional endowments.

Third, establish a coordinated policy system integrating “data-innovation-industry”. On one hand, set up special incentives to support the construction of deeply integrated industry-university-research platforms centered around data, accelerating the industrialization of scientific and technological achievements. On the other hand, leverage the data factor to empower the transformation of traditional industries, precisely cultivate strategic emerging industries and future industries, and drive the overall industrial structure towards higher sophistication and intelligence. This will systematically facilitate the transmission mechanism through which the data factor drives the development of new quality productive forces.

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### Conflicts of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

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