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AN ANALYSIS OF THE INFLUENCE AND MECHANISMS OF THE DIGITAL ECONOMY ON THE DISPARITIES IN URBAN TOTAL FACTOR PRODUCTIVITY

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Abstract. The influence of the digital economy (DE) on the coordination of the urban total factor productivity (TFP) gap and its underlying mechanisms were investigated. The significance of this research mainly originates from its contribution to the theoretical understanding of regional coordination mechanisms, offering new insights into how the digital economy internally regulates disparities in regional TFP. Key findings include: (1) The dynamic analysis reveals that during the early stages of DE, the urban TFP gap expands significantly. However, as the digital economy matures, it contributes to reducing this gap. (2) Quantile regression results indicate that the digital economy substantially narrows the TFP gap primarily in regions with the most pronounced disparities (comprising 20% of the sample), while this effect is not evident in the remaining 80% of regions. (3) Enhancing the level of marketization of factors significantly strengthens the digital economy's ability to reduce the TFP gap, and improvements in resource allocation also contribute to this effect.

Keywords: digital economy, regional TFP gap, factor marketization, resource misallocation.

JEL Classification: O11, O20, O30.

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1. Introduction

As China's digital divide continues to expand, the impact of the digital economy on the coordinated development of different regions presents a complex picture (Ma et al., 2019; Marshall et al., 2020). On one side, the digital economy has contributed significantly to the lowering of information barriers across regions, thereby reducing the impact of geographical separation between the western and central areas. It plays a role in mitigating the imbalances in regional development (Bellofatto & Besfamille, 2021; Li et al., 2017; Piętak, 2022). On the other hand, the extensive adoption of advanced information technologies in economically developed regions has intensified the digital divide, particularly in less developed areas that suffer from a lack of talent, inadequate infrastructure, and policy imbalances (Cavallaro & Dianin, 2022; Everson et al., 2019; Gray et al., 2017). This expanding gap suggests that alongside the vigorous DE, it is crucial to explore effective strategies to reduce regional disparities, thereby fostering the synchronized growth of both the digital and regional economies (Chen et al., 2023). In this context, examining the dynamic effects and transmission mechanisms of DE on the regional TFP gap is essential for achieving balanced economic progress.

However, there has been little investigation of the link between the DE and the TFP gap. Most current research has concentrated on the effects of the digital economy on regional imbalances, primarily examining two areas: the impact of the digital economy on income inequality between different regions and its effect on disparities in regional economic development.

In the first area, research on how the digital economy affects regional income inequality has been explored extensively, but a clear consensus has yet to be reached. One school of thought suggests that the digital economy is inherently inclusive, and sharing nature allows it to provide "latecomer advantages" to residents in less affluent regions. It reduces residents' production costs information asymmetry, increasing their access to financing and entrepreneurial opportunities, thereby increasing income and alleviating income inequality (Mäntymäki et al., 2019; Mayer, 2021). The second perspective argues that underdeveloped regions may lack the necessary resources, labor force quality, infrastructure, and other endowments. This may result in the underutilization of digital dividends, and the existence of the digital divide could widen income inequality (Huebener et al., 2017; Liu et al., 2021; Taylor & Habibis, 2020).

In the second area, concerning the effects of the digital economy on differences in economic development between regions, researchers have largely reached a consensus. It is widely accepted that the digital economy acts as a significant catalyst for regional economic growth and contributes to high-quality development. On the one hand, it acts as a new engine for regional economic growth (Rothstein, 2021; Santoalha et al., 2021). Meanwhile, it is an effective approach for reducing regional development disparities, helping to coordinate and balance regional development disparities (Mahon & Fanning, 2019; Teece, 2018; Wang et al., 2024). However, this research primarily focuses on economic growth, and its impact on narrowing the regional TFP gap has yet to be addressed.

In summary, most existing studies have concentrated on the effects of the digital economy on income and economic developmental differences between regions, but the conclusions drawn have often varied significantly. In addition to the choice of indicators and data used to assess the DE level, the lack of in-depth exploration of the underlying mechanisms also contributes to the mixed findings. A critical question remains: Can the development of the DE narrow the regional TFP gap? If possible, what is its transmission mechanism? Moreover, the academic community has yet to fully investigate the roles of factor marketization and resource mismatch in how the digital economy influences regional disparities in TFP. To address these gaps, our research centers on the regional TFP gap, examining both the impact and mechanisms of DE. By incorporating spatial effects and quantile heterogeneity, we aim to analyze the dynamic impact and transmission mechanisms of DE on regional TFP disparities, with a particular focus on factor marketization and resource mismatch.

The innovation of this article lies in (1) expanding the research perspective. In the context of a widening "digital divide" and significant regional imbalances in the digital economy, most studies have not addressed its effects on the regional TFP gap. This article will shift the focus of research to the level of the urban TFP gap, which not only enriches and deepens the theoretical research on regional coordination mechanisms under the background of the digital economy but also explores the heterogeneity of the digital economy from different levels of regional gap after considering spatial effects. It also provides a theoretical reference for China's balanced economic growth and sustained promotion of shared prosperity. (2) Dig deeper into research. The DE significantly influences the allocation and efficiency of market factors. However, current research has limitations in thoroughly examining the influence of the DE on the transmission mechanisms of factor allocation and the TFP gap. This article approaches the issue from the perspectives of factor marketization and resource mismatch, concentrating on the input and distribution of factors within the context of the original theoretical framework. It deeply examines the digital economy's transmission mechanism and dynamic evolution process on the regional TFP gap, focusing on analyzing its impact mechanism and action path. It further reveals its transmission mechanism, opens up the "black box" of the internal adjustment mechanism of the DE on the regional TFP gap, and provides a path and reliable guidance for regional coordinated development.

2. Analysis of impact mechanisms

Figure 1 illustrates the overall framework for analyzing the mechanism of the TFP gap of cities affected by the digital economy. We first explored the dynamic impact effect, which includes two parts. Firstly, in the early stages of DE, the agglomeration of input factors led to widening regional TFP gaps and even polarization effects. Secondly, the accelerated diffusion of factors can significantly suppress the regional TFP gap in the later stages of DE. Secondly, building on these findings, the mechanisms through which factor marketization and resource mismatch affect the influence of the digital economy were examined. Factor marketization notably enhances the digital economy's capacity to narrow the regional TFP gap by promoting industry and regional collaboration. Similarly, addressing resource mismatch significantly strengthens this narrowing effect. However, the specific mechanisms vary across regions with different levels of TFP. A detailed analysis of these mechanisms is presented in the following Sections.

2.1. General mechanisms

From a dynamic perspective, in the early stages of DE, new internet-based economic formats, digital technology infrastructure, and other attributes of the digital economy concentrated in economically developed areas in the eastern coastal regions of China, such as the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions. This acceleration of capital, talent, and technological innovation factors flowing back from the central and western areas to these regions has resulted in accelerated R&D innovation and increased TFP in developed areas. However, the outflow of talent and technology from underdeveloped areas has hindered the effective enhancement of TFP, leading to a significant widening of regional TFP gaps. There has even been a polarization phenomenon in regions like the Yangtze River and Pearl River Deltas (Xiao et al., 2023). According to the theory of factor agglomeration and transfer, modern information service technologies such as the digital economy allow factors to move more freely and efficiently between different regions, enhancing the flow of resources such as talent, capital, technology, and knowledge from remote, resource-poor,

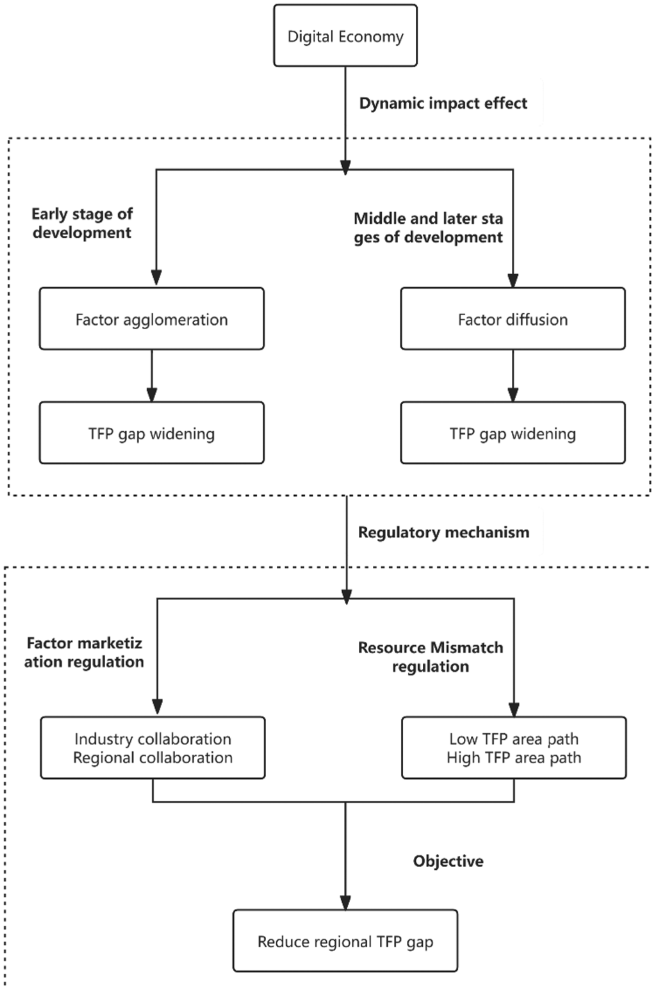

Figure 1. Framework diagram of impact mechanism analysis

and economically less-developed regions to economically developed eastern coastal regions. This strengthens the central region's agglomeration effect, further widening the imbalance in regional TFP (Gallistl et al., 2021; Naslund et al., 2017; Twining, 2021).

In the later stages of DE, to pursue optimal marginal returns, factors tend to move from regions with high production costs to those with low production costs. This results in equalizing average returns in various regions, accompanied by the continuous convergence of regional TFP gaps. With the implementation of the Digital China strategy, digital technology as a universal information technology and data as a universal production factor input is being increasingly applied and strengthened. This will help bridge the digital divide, reduce transaction costs, and promote industry agglomeration, promoting the balance of regional TFP gaps (Fennell, 2022; Ferreira et al., 2021). As digital technology and the real economy become deeply integrated, their breadth and depth gradually deepen. Innovative factors such as talent, information, technology, and data are being shared and circulated among different regions and cities, significantly expanding the spill-over effects of technology and knowledge from developed regions to less developed regions. This reveals a stronger spatial positive correlation. This, in turn, enhances the efficiency of input factors, quality, and allocation in less developed regions, improving their TFP (Gebremichael & Jackson, 2006; Li et al., 2024).

In summary, in the early stages of DE, the concentration of input factors leads to the widening of regional TFP gaps, even resulting in polarization. However, in the later stages of DE, the accelerated diffusion of factors can significantly suppress these gaps. The present study proposes this Hypothesis:

H1: *The relationship between DE and regional TFP gaps exhibits a "U-shaped" dynamic evolution.*

2.2. Market-based mechanisms for regulating factors

Regarding industry collaboration, due to its shared, technological, and inclusive nature, the digital economy enhances mutually beneficial mechanisms among industries. This allows various industries to accelerate the sharing and flow of data, technology, talent, and other production factors, thereby promoting the coordinated development of manufacturing and service industries (Hattori et al., 2021). In addition, the digitized economy can reduce industry monopolization and narrow the productivity gap between industries. Specifically, a region often focuses on developing critical industries based on resource advantages. The government provides incentives and preferences regarding tax policies, fiscal allocation, land transfers, and other areas, resulting in a monopoly of input factors within that industry. The digital economy helps alleviate factor monopolies, expedite the marketization of factors, and facilitate the free flow between different industries, such as between service and manufacturing, high- and low-tech, and primary and leading industries. This is beneficial for balancing TFP development across industries (Liow et al., 2018).

In regional collaborations, the rapid DE significantly increases the marketization level for factors through information spill-over, knowledge spill-over, and technology spill-over effects. This increased level of marketization can lower the costs of cross-regional factor movement and enhance regional TFP spill-over effects, thus promoting collaborative development across regions and reducing the overall productivity gap (Aromi & Clements, 2019; Meegan et al., 2018). At the micro-level, economic entities in various regions, such as enterprises, gradually move toward open and flat directions in the wave of digital economic reform. On the one hand, they utilize technologies like digital communication to reduce communication costs between various companies and departments, facilitating the efficient collaboration of departments such as sales, products, and markets by streamlining the flow of information, data, and other transmission channels. On the other hand, through the free movement of talent, data, and other resources between regions, they accelerate production iterations, achieve resource sharing among companies from different sectors and regions, and enhance the coordinated development of regional enterprises (Heim et al., 2019). At the intermediate level, reforms in factor marketization enable factors to have a crucial influence within the market economy. This enables various factors to move quickly and smoothly between different regions and industries, significantly impacting breaking factor monopolies, narrowing industry gaps, and harmonizing the regional TFP gap (Wang et al., 2020). On the macro level, the most direct effect of factor marketization is to balance factor prices between regions, thereby avoiding the agglomeration of factors due to significant differences in regional production factor prices, which can lead to surpluses and shortages of factors and ultimately balance the TFP gap across regions (Wang et al., 2021a).

Accordingly, Hypothesis 2 is proposed:

H2: *Factor marketization significantly enhances the ability of the digital economy to reduce the regional TFP gap.*

2.3. Resource mismatch adjustment mechanisms

Improvements in the degree of resource misallocation and optimized factor allocation contribute to balancing the TFP gap across regions. Specifically, firstly, optimized factor allocation can significantly enhance factor structure, actively releasing the "structural kinetic energy" of factors. During the early stages of economic development, labor and capital tended to aggregate in the eastern regions where returns on factors are higher due to their geographical concentration. This leads to a significant gap in TFP between eastern and western regions. However, as digital technology enhances factors' accessibility and utilization through data sharing and information transmission, it also lowers the traditional barriers to economic organization. It reduces the cost of factor movement and transactions. These dynamics result in the inflow of factors back to western regions, facilitating factor allocation throughout the country (Liu et al., 2017). Secondly, the inflow of factors into the western regions significantly stimulates economic vitality and creativity in underdeveloped regions. With the population returning from the eastern regions, there is a basis for various economic reform dynamics, including capital, technology, and advanced management concepts. These dynamics can significantly drive economic and efficiency reforms in underdeveloped regions in western China (Mocetti & Orlando, 2019). Thirdly, improving the degree of resource misallocation helps balance factor pricing across regions, promoting equal and reasonable exchange of regional factors. This effectively alleviates the problem of regional development imbalance caused by asymmetric labor and land prices between the eastern and western areas (Hur et al., 2019; Li et al., 2021).

However, improving resource misallocation significantly enhances the ability of the digital economy to reduce the regional TFP gap. However, the pathways to improvement differ between regions with high and low TFP levels. Specifically, in regions with low TFP levels in China's western regions and an excess of surplus labor relative to those in the east, the digital economy alters the industrial structure of the western regions, mainly rural areas. It enriches their employment opportunities, promoting the migration of surplus labor to the eastern regions. While this weakens the impact of improved labor allocation on the TFP gap in the eastern regions, it also leads to the outflow of surplus labor, the return of highly skilled workers to the eastern regions, and an increase in urbanization in the western regions. This, in turn, enhances their TFP levels (Wang et al., 2021b; Zheng et al., 2021).

From the perspective of optimizing capital allocation, the eastern regions have an initial advantage in terms of capital compared to the western regions. The digital economy can enhance capital accessibility in low TFP regions while optimizing capital allocation, which can significantly increase the flow of urban capital, improve urban-rural capital misallocation, and help narrow the TFP gap in low-productivity regions. Additionally, research has suggested a marked causal association between human capital levels and agricultural TFP (Tijdens et al., 2018; Tran et al., 2019). Therefore, compared to the western regions, the eastern regions possess the prerequisites for bridging the TFP gap under the optimized capital allocation perspective, given their comparative advantages in capital, human resources, and other factors. This implies that, from a capital allocation perspective, the DE significantly narrows the TFP gap only in the eastern regions (Wang et al., 2020).

Consequently, Hypothesis 3 is proposed as follows:

H3: *Improvements in resource misallocation significantly enhance the digital economy's ability to reduce the regional TFP gap, but the mechanisms differ in regions with different TFP levels.*

3. Empirical strategy, variable selection, and data description

3.1. Empirical strategy

Usually, without significant events, regional economic development is a long-term and sustained process, and changes in TFP also conform to this characteristic. In other words, the previous period's TFP generally positively impacted the current period's TFP. At the same time, specific regions do not experience significant changes in production factors such as capital and technology over some time, and production, consumption, and economic structure generally remain stable. This leads to minimal fluctuations in regional TFP in the short term. Therefore, within a certain period, the TFP of a particular region has time inertia. To explore whether the digital economy can significantly shrink the regional TFP gap and its impact mechanism, we first construct a dynamic panel regression model as shown in Equation (1):

$$GAP\_TFP_{it} = \alpha_0 + \alpha_1 DEI_{it} + \alpha_2 GAP\_TFP_{it-1} + \alpha_j \boldsymbol{X_{it}} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where represents cities; t represents periods; the TFP gap of the city is periodic; the level of DE of the city in period t is DEI_{it}; and the first-order lag term of the TFP gap of cities is GAP_TFP_{it-1}. Vector is several control variables that may affect regional TFP gaps. μ_i is the city-fixed effect γ_t, is the time-fixed effect, and ε_{it} is the random error term. α_1 is a coefficient reflecting the DE level, which is the core explanatory variable coefficient of the paper.

For model (1), the paper primarily employs the generalized method of moments (GMM) to estimate the unknown parameters in the dynamic panel regression model. The commonly used GMM methods include system GMM and difference GMM. While the dynamic panel model incorporates lagged dependent variables to enhance its dynamic explanatory power, this approach also introduces potential endogeneity issues. Numerous studies have confirmed that differential generalized moment estimation methods have the problem of missing variables, while system generalized moment estimation methods can overcome the endogeneity problem of the model to the maximum extent. Therefore, this article chooses the system GMM method for modeling analysis. Afterward, this article chooses to construct the Hansen test statistic to examine the validity of instrumental variables.

Based on the mechanism analysis, we introduce the quadratic term of the level of DE into the model to analyze its nonlinear effects on the regional TFP gap further. Thus, we construct Model (2):

$$GAP\_TFP_{it} = \alpha_0 + \alpha_1 DEI_{it} + \alpha_2 DEI_{it}^2 + \alpha_3 GAP\_TFP_{it-1} + \alpha_j \boldsymbol{X_{it}} + \mu_i + \gamma_t + \varepsilon_{it}. \quad (2)$$

α_2 is the coefficient of the secondary term of the level of digital economic development, and significant indicates that the impact of digital economic development on the regional TFP gap there is a "positive U-shaped" relationship, and significant indicates that the impact of digital economy development on regional TFP gap there is an "inverted U-shaped" relationship.

To further investigate the influence and mechanism of transmission of the digital economy on the regional TFP gap based on the perspectives of factor marketization and resource misallocation, we incorporate factor marketization, resource misallocation, the DE level, and their interaction terms into the Model (2) and construct the moderation effect models as shown in Equations (3) and (4):

$$GAP\_TFP_{it} = \alpha_0 + \alpha_1 DEI_{it} + \alpha_2 DEI_{it}^2 + \alpha_3 MARKE_{it} + \alpha_4 MARKE_{it} \times DEI_{it} + \alpha_5 MARKE_{it} \times DEI_{it}^2 + \alpha_j \boldsymbol{X_{it}} + \mu_i + \gamma_t + \varepsilon_{it}; \quad (3)$$

$$GAP\_TFP_{it} = \alpha_0 + \alpha_1 DEI_{it} + \alpha_2 DEI_{it}^2 + \alpha_3 MISMATCH_{it} + \alpha_4 MISMATCH_{it} \times DEI_{it} + \alpha_5 MISMATCH_{it} \times DEI_{it}^2 + \alpha_j \boldsymbol{X_{it}} + \mu_i + \gamma_t + \varepsilon_{it}. \quad (4)$$

The two Equations above have identical structures. To investigate the moderating effects of factor marketization and resource misallocation in the mechanism involved in transmitting the effect of the digital economy on the regional TFP gap, we include interaction terms of both factor marketization and resource misallocation with the level of DE. To explore how factor marketization and resource misallocation affect and change the nonlinear characteristics of the effect of the digital economy on the regional TFP gap, we include interaction terms of both factor marketization and resource misallocation with the quadratic term of DE. These Equations represent the level of factor marketization for the city in period and the degree of resource misallocation for the city i in period t.

Finally, research has shown that spatial effects play a significant role in forming and developing regional economic disparities (Ali et al., 2018; Ma & Zhu, 2022). We introduce three models, namely the Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Spatial Autoregressive Model (SAR), to capture spatial effects and use them to perform robustness checks on the empirical results. The spatial weight matrix is obtained as follows.

The first step constructs a geographic proximity matrix:

$$W_d = \begin{cases} 1/d_{i,j}, & i \neq j \\ 0, & i = j \end{cases}. \quad (5)$$

The distance between the city and city j is $d_{i,j}$, is measured using the geographic distance between the seat of the municipal government of each city. The distance between the municipality and the rest of the cities is measured using the distance between the seat of the municipal government of the municipality and the seat of the government of the rest of the cities. The distance between municipalities and other cities is measured by the distance between the seat of the municipal government of the municipality and the seat of the government of the remaining cities, and the distance measure is taken from the national 1:300 GIS database.

The second step constructs a matrix of similar economic development situations:

$$W_e = \begin{cases} 1/\left|\overline{E_i} - \overline{E_j}\right|, & i \neq j \\ 0, & i = j \end{cases}, \tag{6}$$

where denotes the per capita GDP of each city in 2010–2020 as a measure of the city's economic development level and deflated with 2010 per capita GDP as the base period price.

The third step constructs a comprehensive weight matrix:

$$W_{d-e} = \eta W_d + \left(1-\eta\right) W_e, \tag{7}$$

where η is the adjustment factor, take η = 0.5.

3.2. Selection of variables and description of the data

(1) Dependent variable: Urban TFP gap (*GAP_TFP*). Existing mainstream literature needs an authoritative measure of the urban TFP gap. We use the absolute value of the disparity between a city's TFP and the maximum TFP for that year, multiplied by 100, as a proxy variable for the urban TFP gap. The measurement of urban TFP is based on the DEA-Malmquist method, representing a combination of the Data Envelopment Analysis (DEA) and the Malmquist Index. Data sources include the "China Statistical Yearbook" (National Bureau of Statistics, n.d.-a), provincial and city statistical yearbooks (China Statistical Database, n.d.), "China Population and Employment Yearbook", (n.d.) and "Compilation of China's Statistical Data" (National Bureau of Statistics, n.d.-b).

(2) Core independent variable: DE Index (*DEI*) refers to the "Statistical Classification of Digital Economy and Its Core Industries" we characterize and measure urban-level digital economy in terms of three dimensions, namely, digital industrialization, industry digitalization, and digital governance. Specifically, the analysis explores urban-level digital industrialization through various aspects such as digital users, digital employment, and digital output. Data are drawn from the "China City Statistical Yearbook" (China Statistical Database, 2023) and include year-end figures for mobile phone users, internet broadband subscribers, employees in the computer, information, and software industries, as well as revenue from telecommunications businesses. Regarding urban-level industry digitalization, this study mainly uses digital finance indicators. These indicators are completed jointly by Peking University and Alibaba Group, including coverage, amount of digital support, and depth of use. We use the comprehensive index of government electronic service capacity for urban-level digital governance. Data comes from the "Government Electronic Service

Capacity Index Report" (Hu et al., 2023). The project evaluates electronic service channels such as government websites, government Weibo, government WeChat, and government apps, constructing a comprehensive index of government electronic service capacity that can comprehensively reflect the development level of government electronic service capacity. Using these dimensions, a digital economy index was constructed for 285 Chinese cities spanning from 2010 to 2022 through principal component analysis. This index was then utilized for empirical analysis.

(3) Moderator variable 1: Level of factor marketization (*MARKE*). Considering that factor marketization includes multiple aspects such as land, labor, capital, technology, and data, a single indicator may only partially and comprehensively reflect the connotation of China's factor marketization. We decide to use the "Chinese Provincial Marketization Index Report (2021)," which compiles statistical indices to score, rank, and comprehensively evaluate the level of factor marketization in 31 provinces in China from 1997 to 2022. It is more comprehensive in coverage and has higher comparability horizontally across cities and vertically across time. Data for this section is from the "China Provincial Marketization Index Database, n.d.". As the database only contains provincial-level data, we used the same calculation method and process as the database to calculate the marketization level of factors at the city level in each region.

Moderator variable 2: Degree of resource misallocation (*MISMATCH*). Resource misallocation refers to the inefficient allocation of production inputs across production sectors, such as capital and labor. In the context of the Chinese market, enterprises in various regions and industries often obtain production inputs at prices that are either undervalued or overvalued, and this is typically manifested as price misallocation of production factors in the Chinese market. Therefore, we measure the degree of resource misallocation by the ratio of the primary input factor's fair value to its actual price. In addition, in China's current economic development context, labor and capital are the most significant components of production inputs for most enterprises. Therefore, we use the degree of capital misallocation (*mis K*) and labor misallocation (*mis L*) to measure the degree of resource misallocation in each city. This can be expressed as follows:

The Cobb-Douglas production function (C-D production function) was initially developed to assess the degree of capital-labor mismatch in each city (Helpman et al., 2004).

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L. \tag{8}$$

Log the above Equation:

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L.$$

Following the standard definition, where Y represents gross output, this paper uses the GDP value add of each city as a measure. K represents capital input, measured by the net fixed investment of each city, and L is labor input, quantified by the employee numbers in each city. The three variables are expressed in logarithmic form. In addition, A represents technological progress, while α and β are the output elasticity of capital and labor, respectively. Taking the logarithm of Equation (8) and establishing a general linear regression model can derive the output elasticity of technical progress, capital, and labor.

The marginal outputs of capital and labor are calculated by taking the partial derivatives of K and L, respectively:

$$MP_K = A\alpha K^{\alpha-1}L^{\beta} = \alpha Y/K; \tag{9}$$

$$MP_L = A\beta K^{\alpha}L^{\beta-1} = \beta Y/L. \tag{10}$$

Finally, the degree of capital mismatch and the degree of labor mismatch are respectively:

$$mis\,K = MP_k/r; \tag{11}$$

$$mis\,L = MP_L/w, \tag{12}$$

where r is the price of capital, expressed using the central bank's one-year lending rate, by the standard methodology, and w is the price per unit of labor, expressed using the ratio of total wages to the total number of employees.

(4) Control variables: We have selected the following relevant variables that may affect the urban TFP gap as control variables to mitigate endogeneity issues in the model (Felbermayr & Jung, 2018; Frey & Osborne, 2017; Lin et al., 2018): Entrepreneurship Activity (*CREATION*), Human Capital Level (*HUMAN*), Regional Research and Development Investment (*R&D*), Degree of Openness (*OPEN*), Capital Level (*CAPITAL*), and Urbanization Level (*CITY*).

Table 1 presents the essential statistical characteristics of the main variables, including the dependent variable, core independent variable, mediator variables, and control variables. There are no outliers in each variable, and they are within a reasonable range, basically in line with the requirements for subsequent econometric analysis.

Table 1. Main variable descriptive statistics

Variable type	Variable symbol	Variable meaning	Calculation method	Mean value	Standard deviation	Maximum value	Minimum value
Explained variables	*GAP_TFP*	Regional TFP Gap	The absolute value of the difference between the city's TFP and the city with the highest TFP for the year*100	4.880	3.422	10.407	0
Explanatory variables	*DEI*	City DEI	The authors measured by constructing the index system	0.286	0.198	0.871	0.057
Moderating variables	*MARKE*	Factor marketization level	The total marketization index	0.023	0.1168	0.5527	-0.401
	mis K	Degree of capital mismatch	Calculated by the authors	0.409	0.105	0.902	0.053
	mis L	Degree of labor mismatch	Calculated by the author	3.038	2.823	22.617	0.762

End of Table 1

Variable type	Variable symbol	Variable meaning	Calculation method	Mean value	Standard deviation	Maximum value	Minimum value
Control Variables	*CREATION*	Level of entrepreneurial activity	The ratio of the number of new private enterprise legal entities to the total number of new enterprise legal entities per year	0.605	0.028	0.917	0.481
	HUMAN	Level of human capital	The ratio of the population with a university degree or above to the total population by region	2.127	4.182	35.302	0.513
	R&D	Regional R&D investment	The ratio of R&D Expenditure to GDP	1.812	0.956	3.045	0.570
	OPEN	Degree of openness to the outside world	The ratio of total regional import and export trade to GDP	0.018	0.061	0.492	0.002
	CAPITAL	Level of capital	The loan balance of financial institutions divides by the deposit balance	0.822	0.047	0.940	0.521
	CITY	Level of urbanization	The ratio of urban household population to total population at the end of the period	64.722	6.041	88.100	11.142

4. Results and discussion

4.1. Regression analysis

4.1.1. Benchmark regression

Figure 2 displays changes in TFP gaps in China and its eastern, central, and western regions from 2010 to 2022. We can visually observe the following key features: First, an analysis of the temporal trend reveals that the TFP gaps across Chinese regions generally follow an inverted U-shaped pattern, with an initial widening of the gap followed by a gradual narrowing. Second, from a spatial perspective, the TFP gaps among Chinese regions typically follow a developmental hierarchy: the western region exhibits the largest gaps, the central region shows moderate gaps, and the eastern region has the smallest TFP gaps.

Table 2 illustrates the baseline regression results on the influence of DE on the regional TFP gap. In column (1), which serves as a control group, a static panel model with time and entity-fixed effects is constructed based on Model (1), estimated using OLS. Column (2) represents a dynamic panel model without control variables and the quadratic term of the DEI, estimated using the GMM method. To examine the linear relationship between DE and regional TFP gap, column (3) uses the dynamic panel model based on Model (2) with control variables include but without the quadratic term of the DE index, also estimated using the GMM method. Column (4) represents the main regression outcomes, evaluating the impact

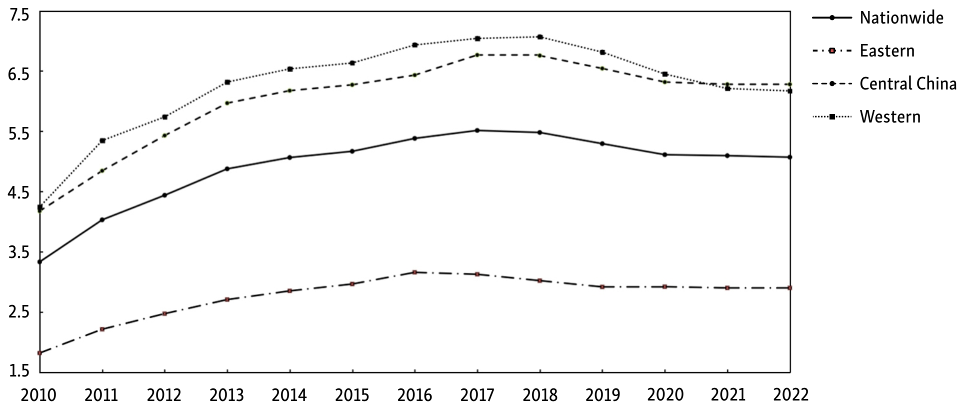

Figure 2. Changes in the TFP gap between Eastern, Central, and Western regions

of DE on the regional TFP gap by constructing Model (3) and including all control variables and the quadratic term of the DE index. The results demonstrate that:

① In column (3), we analyze the linear effect of urban digital economic development on the TFP gap. Overall, the coefficient of the core explanatory variable, the DE level, is 0.281, which is significant at the 1% level. The analysis suggests that, if we consider the entire period from 2010 to 2022, DE fails to reduce the regional TFP gap and contributes to a significant increase in the gap.

② In column (4), the analysis explores the nonlinear effects of DE on the regional TFP gap. Firstly, aligning with the findings in column (3), the coefficient for the first-order term of DE is 0.260, which is significant at the 5% level, confirming that DE does not help in narrowing the regional TFP gap. Secondly, the system GMM estimates show that the coefficient for the first-order lag of the regional TFP gap is 0.221 and significant at the 1% level, indicating some inertia in the changes of regional TFP. Lastly, incorporating the quadratic term of the DE index into the baseline model to assess the nonlinear impact reveals that the coefficient of this quadratic term is –0.192, which is significant at the 1% level. This finding confirms a significant inverted-U relationship between DE and the regional TFP gap, thereby validating Hypothesis 1 within the theoretical framework.

The above conclusions differ from the current mainstream literature research findings, which generally believe that digital technology and the DE can help narrow regional economic disparities and reduce regional TFP levels through technology spillovers and other means (Santoalha et al., 2021; Zheng et al., 2021). On the contrary, this article concludes that the current era of DE has not effectively narrowed the regional TFP gap but significantly widened the TFP gap between cities. Based on existing research, we summarize the reasons as follows.

The digital economy also faces digital divide and imbalance issues in different regions and development periods. In other words, the Kuznets curve of income distribution imbalance is equally applicable to the DE effects on regional TFP disparities (Deutsch & Silber, 2004; Stern et al., 1996). Kuznets explored the impact of economic development on household income distribution and demonstrated that during rapid economic growth and insufficient development, the income distribution gap among residents will continue to widen with economic growth, and the faster the growth rate, the more obvious the gap. This situation has been verified in emerging economies, especially developing countries (Nguyen & Zhao, 2021). However, as economic development gradually becomes stable and sufficient, the income gap among residents also narrows until it theoretically tends to be the same, and this situation is also beginning to show signs in developed economies (Jalil, 2012). Although this theory was first applied to the study of changes in income inequality among residents during the transition from agricultural countries to developed industrial countries, it also has strong explanatory power for the issue of regional TFP disparities in the digital economy of emerging economies.

On the whole, in the early stage of the DE, the advantageous resources of the digital economy, such as the new formats of the Internet economy and the construction of digital technology infrastructure, gathered in the eastern coastal areas and the economic circles of developed cities, such as Beijing Tianjin Hebei, the Yangtze River Delta, and the Pearl River Delta, resulting in an agglomeration effect, which accelerated the return of innovative factors, such as capital, talent, and technology, from the central and western regions to the above regions. On the one hand, it accelerated the R&D innovation and TFP improvement in developed regions, while on the other hand, the outflow of talent, technology, and other factors, led to the long-term failure to effectively improve the TFP in underdeveloped regions, which significantly widened the provincial TFP gap (Benitez et al., 2022). In the later DE stages, with the implementation of the Digital China strategy, digital technology as a universal information technology tool and data as a universal production factor input, the inherent universality, inclusiveness, and sharing characteristics of the digital economy are constantly mentioned and strengthened, which are beneficial for bridging the digital divide, reducing transaction costs and industrial agglomeration, and helping to balance the regional TFP gap (Harpriya et al., 2022). Furthermore, with the deep integration of digital technology and the real economy, its breadth and depth are gradually developing towards depth. Innovative elements such as talent, information, technology, and data can be shared and flowed between different regions and cities, significantly expanding developed regions' technology and knowledge spillover effects on underdeveloped regions and showing a clear spatial positive correlation. This, in turn, optimizes the quantity, quality, and allocation efficiency of input factors in underdeveloped regions to improve their TFP (Vu & Hartley, 2022).

Based on the evident inverted-U relationship between DE and the regional TFP gap, we conduct further in-depth discussions. Taking column (4) as a reference, where all control variables, the quadratic term of the DE index, and the lagged term of the regional TFP gap are include in the GMM model estimation, we calculate that the turning point of the inverted-U curve is 0.67. This implies that when the digital economic index is to the left of the turning point, it does not help reduce the regional TFP gap and significantly widens it. However, when the digital economic index is to the right of the turning point, digital economic development contributes to balancing and coordinating the differences in the regional TFP gap. As indicated in the "Main Variable Descriptive Statistics" section, the range of the explanatory variable, the urban DE index, falls within [0.057, 0.871]. This suggests that during the study period (2010–2022), early-stage DE did not inhibit the increase in the regional TFP gap. In contrast, in the later stage of DE, it helps balance and coordinate the differences in the regional TFP gap.

Table 2. Baseline estimations of the impact of DE on regional TFP gap

Variables	Control group (fixed effects static panel) (1)	System GMM (control variables and quadratic terms not add) (2)	System GMM (control variables add but no quadratic terms) (3)	System GMM (4)
GAP_TFP_{it-1}	—	0.265*** (0.074)	0.237*** (0.086)	0.221*** (0.076)
DEI	0.287*** (0.048)	0.275** (0.132)	0.281*** (0.070)	0.260** (0.116)
DEI^2	—	—	—	–0.192*** (0.072)
CREATION	0.084 (0.092)	—	0.076* (0.048)	0.071* (0.038)
HUMAN	0.141*** (0.028)	—	0.121** (0.058)	0.100*** (0.041)
R&D	0.193*** (0.040)	—	0.199*** (0.052)	0.184*** (0.033)
OPEN	–0.036** (0.016)	—	–0.049*** (0.012)	–0.031*** (0.007)
CAPITAL	–0.204** (0.094)	—	–0.224* (0.125)	–0.204*** (0.038)
CITY	0.030 (0.083)	—	0.021* (0.014)	0.007 (0.094)
Region fixed effects	Fixed	Fixed	Fixed	Fixed
Time fixed effects	Fixed	Fixed	Fixed	Fixed
R^2	0.246	0.178	0.164	0.118
AR(1)test	—	–1.97 (0.022)	–1.88 (0.027)	–1.76 (0.030)
AR(2)test	—	–0.47 (0.081)	–0.44 (0.076)	-0.46 (0.070)
Hansen test	—	41.69 (0.792)	39.87 (0.783)	36.94 (0.786)

Note: 1. Except for the last three rows, the values in parentheses are standard errors, and the values in parentheses in the last three rows correspond to the P-values of AR (1), AR (2), and Hansen tests, respectively. 2. "*", "**", and "***" represent significance at the 10%, 5%, and 1% levels, respectively.

4.1.2. Considering spatial effects

Table 3 provides the estimation outcomes after introducing the SEM, SDM, and SAR models to capture spatial effects. The results reveal the following findings: A positive spatial autocorrelation in the regional TFP gap among Chinese cities indicates a significant clustering effect. On the other hand, most coefficients remain consistent with the previous results, particularly in the case of nonlinear regression. This provides compelling evidence that digital economic development fails to reduce the regional TFP gap and, to some extent, significantly widens the gap. This result further reinforces an inverted-U relationship between DE and the regional TFP gap.

Table 3. Estimation results after considering spatial effects

Variables	SEM (1)	SDR (2)	SAR (3)
ρ/λ	0.635*** (0.162)	0.594*** (0.168)	0.638*** (0.125)
$GAP\_TFP_{it-}1$	0.022*** (0.030)	0.020*** (0.027)	0.017*** (0.012)
DEI	0.278** (0.032)	0.281*** (0.025)	0.274** (0.031)
DEI^2	–0.151*** (0.013)	–0.149** (0.011)	–0.153*** (0.022)
R^2	0.217	0.206	0.212
Log-Likelihood	896.22	924.31	907.50

Note: Values in parentheses are standard errors; "*," "**," and "***" represent significant at 10%, 5%, and 1% significance levels, respectively.

4.1.3. Quantile regression

The previous Section examined the overall DE impact on the regional TFP gap. However, given the marked disparities in economic development between different regions in China and the substantial heterogeneity in TFP, we continue to assess the influence of the digital economy on the regional TFP gap in different quantiles. In this Section, we divide the sample regions into four categories based on the gap level: low gap (regions with a TFP gap below the 20th percentile of the total sample), low-medium gap (regions with a TFP gap between the 20th and 50th percentiles of the total sample), medium-high gap (regions with a TFP gap between the 50th and 80th percentiles of the total sample), and high gap (regions with a TFP gap above the 80th percentile of the total sample).

As shown in Table 4 below, we continue to use the GMM regression method for estimation. The principal findings were:

In the low, low-medium, and medium-high gap samples, the estimated coefficients of the digital economy showed positive significance at the 5% level, demonstrating that in regions

Table 4. Quantile heterogeneity results of the digital economy on regional TFP gap

	DEI	Region fixed effects	Time fixed effects	R^2
Low gap (below 20% quartile)	0.194** (0.765)	Fixed	Fixed	0.59
Medium-low gap (20–50% quantile points)	0.278** (0.932)	Fixed	Fixed	0.43
Medium-high gap (50–80% quantile points)	0.321*** (0.780)	Fixed	Fixed	0.63
High gap (above 80% quantile)	–0.152*** (0.956)	Fixed	Fixed	0.51

Note: Values in parentheses are standard errors; "*," "**," and "***" represent significant at 10%, 5%, and 1% significance levels, respectively.

with a TFP gap below the 80th percentile, the digital economy not only fails to narrow the regional TFP gap but also has an enlarging effect on it. In contrast, in the high gap sample, the estimated coefficient of the digital economy showed negative significance at the 1% level, suggesting that in regions with a TFP gap above the 80th percentile, the digital economy has a narrowing impact on the regional TFP gap.

In summary, the DE impact on the regional TFP gap varies with the level of the gap. It can significantly reduce the TFP gap only in regions with the most substantial disparities (comprising 20% of the total sample). It has no effect in most other regions (comprising 80% of the total sample).

4.2. Tests for robustness

4.2.1. Replacement of important variables

Table 5 presents the model estimation results after replacing important dependent and independent variables. Columns (1), (3), (5), (7) represent the control group, based on Model (1) with a time-fixed two-way static panel model, estimated using OLS (Ordinary et al.); Columns (2), (4), (6), (8) are estimated using the System GMM method. (1)–(2) columns represent the estimated results after re-measuring regional TFP using the Stochastic Frontier Analysis (SFA); (3)–(4) columns show the results after replacing regional TFP with social labor productivity; (5)–(6) columns present the results after measuring the level of DE by the ratio of total telecommunications business volume to GDP in each region; (7)–(8) columns reveal the results after replacing the DE index with the digital economic index from Tencent's annual "Digital China Index Report" (Tencent Research Institute, 2023).

From the re-estimated results in Table 5, we can observe the following: Firstly, in both the experimental and control groups, the coefficient for DE shows positive significance, at least at the 5% level, reflecting that if we consider the entire period from 2010 to 2020, DE not only fails to narrow the regional TFP gap but also contributes to a significant increase in regional disparities, consistent with the previous findings. Secondly, after using the four methods to replace essential variables, the re-estimated results consistently show that the DE quadratic term coefficient shows negative significance, at least at the 10% level. This implies a significant "inverted U-shaped" correlation between DE and the regional TFP gap, which aligns with the earlier results. Lastly, we observe that the DE index falls on both sides of the "inverted U-shaped" curve, indicating that during the study period (2010–2022), DE in the early stages did not restrain increases in the regional TFP gap. Still, in the subsequent stages, it helped balance and coordinate the disparities in TFP among different regions. Based on this comprehensive discussion, this study considers the empirical results presented earlier robust and reliable.

Table 5. Robustness tests: replacing important variables

Variables	SOFA		Social labor productivity		Ratio of telecommunication turnover to GDP		Digital China Index Report	
	Control (OLS) (1)	Test (GMM) (2)	Control (OLS) (3)	Test (GMM) (4)	Control (OLS) (5)	Test (GMM) (6)	Control (OLS) (7)	Test (GMM) (8)
GAP_TFP_{it-1}	—	0.318** (0.144)	—	0.405*** (0.074)	—	0.302*** (0.068)	—	0.292*** (0.066)
DEI	0.307** (0.137)	0.258*** (0.072)	0.182** (0.084)	0.179*** (0.063)	0.247** (0.117)	0.208*** (0.057)	0.255** (0.115)	0.187** (0.082)
DEI^2	—	–0.183*** (0.062)	—	–0.137*** (0.048)	—	–0.145* (0.084)	—	–0.155** (0.068)
Region fixed effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Time fixed effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
R^2	0.27	0.21	0.17	0.18	0.20	0.17	0.15	0.13
AR(1)test	—	–1.88 (0.031)	—	–1.73 (0.049)	—	–1.94 (0.027)	—	–1.90 (0.026)
AR(2)test	—	–0.52 (0.078)	—	–0.55 (0.079)	—	–0.50 (0.068)	—	–0.57 (0.080)
Hansen test	—	46.37 (0.803)	—	41.38 (0.740)	—	39.52 (0.712)	—	31.08 (0.684)

Note: 1. Except for the last three rows, the values in parentheses are standard errors, and the values in parentheses in the last three rows correspond to the P-values of AR (1), AR (2), and Hansen tests, respectively. 2. "*", "**", and "***" represent significance at the 10%, 5%, and 1% levels, respectively.

4.2.2. Constructing instrumental variables

We employ two methods for the construction of instrumental variables. Firstly, we use the lagged DE index and the interaction term between the previous year's internet users per region (logged) as an instrument for the digital economic index (*DEI*×*INTERNET*). The second method, inspired by Nunn and Qian's research (Nunn & Qian, 2014), involves using the 1995 cross-sectional data of fixed telephones per 100 people in each region and the logged fixed capital investment in the computer service and software industry from the previous year as an instrument for regional digital economic development (*TELE*×*INVEST*).

Table 6 presents the estimation results obtained by constructing instrumental variables and applying a 2SLS model. Column (1) shows the results of the first-stage estimation and column (2) displays the results of the second-stage estimation, with the dependent variable being the regional TFP gap. Before discussing the model's estimation results, the effectiveness of the instrumental variables is discussed.

Weak instrument tests in column (1) indicate that the Cragg-Donald Wald statistic is 74.13, more significant than its Stock-Yogo critical value at a 10% level of significance (16.50), rejecting the null hypothesis of weak instruments in the model. The endogeneity test reveals

Table 6. Robustness tests: Instrumental variables

Variables	Phase I	Phase II
	DEI (1)	*GAP_TFP* (2)
DEI	—	0.283** (0.127)
IV1(*DEI*×*INTERNET*)	0.107* (0.059)	—
IV2 (*TELE*×*INVEST*)	0.063*** (0.017)	—
Individual fixed effects	Fixed	Fixed
Time fixed effects	Fixed	Fixed
Weak instrumental variables test	Cragg-Donald Wald: **74.13** Stock-Yogo: **16.50**	—
Endogeneity tests	Durbin-Wu-Hausman P: **0.053**	—
Over-identification test	—	Sargan P: **0.584**
R^2	0.30	0.22

Note: Values in parentheses are standard errors; "*," "**," and "***" represent significant at 10%, 5%, and 1% significance levels, respectively.

that the Durbin-Wu-Hausman statistic has a p-value of 0.053, which is below 0.1, allowing rejection of the null hypothesis that the instrumental variables are exogenous. Moreover, the overidentification test results in column (2) show that the Sargan statistic's corresponding p-value is more significant than 0.1 (0.584). Thus, we conclude that there is no overall issue of overidentification with the instrumental variables.

The 2SLS regression results using instrumental variables indicate that the coefficient of the dependent variable, the regional TFP gap, shows positive significance, at least at the 10% significance level, indicating that considering the period from 2010 to 2020, digital economic development fails to reduce the regional TFP gap and exacerbates it to a certain extent. This conclusion aligns with the previous findings. In summary, this article considers the empirical results presented earlier robust and reliable. Additionally, compared to the GMM model's estimation results in the empirical section, the coefficient for DE is more significant in the instrumental variable 2SLS model, suggesting that endogeneity issues in the original model may have underestimated the impact of DE on the regional TFP gap.

5. Regulatory mechanism: factor marketization and resource mismatch perspectives

5.1. Testing the adjustment mechanism – factor marketization

Table 7 illustrates the findings from examining the factor marketization adjustment mechanism. Specifically, columns (1) and (3) provide estimations excluding control variables, whereas columns (2) and (4) include the control variables. The analysis centers on exploring how factor marketization mediates the relationship between DE and the regional TFP gap.

Firstly, the coefficient for the level of factor marketization is –0.179, showing significance at the 1% level. This observation indicates that a higher level of factor marketization substantially reduces the regional TFP gap, supporting the hypotheses outlined earlier in the study.

Secondly, the coefficient for the interaction between the digital economy and the level of marketization is positive, with significance at the 10% level, while the squared term of this interaction coefficient is negative, with significance at the 5% level. The observation aligns with earlier empirical findings, indicating that even after accounting for factor marketization, the correlation between DE and the regional TFP gap continues to exhibit a "U-shaped" nonlinear effect.

Thirdly, after introducing factor marketization factors, the turning point of the "U-shaped" curve for the DE impact on the regional TFP gap is 0.41. This value is significantly lower than the turning point in the baseline regression (0.67). The shift in the turning point suggests that increasing factor marketization levels significantly enhance the contribution of the digital economy to reducing the regional TFP gap. Meanwhile, the interaction between the digital economy and factor marketization substantially narrows the range of expansion of the regional TFP gap by the digital economy and enhances the balancing and coordination effects on the regional TFP gap, thereby confirming Hypothesis 2 in the theoretical mechanism.

Previous research has predominantly concentrated on the DE effects on the circulation and allocation of factors, with consistent findings that the digital economy facilitates the free movement of factors through information and technology spillovers (Canh et al., 2020; Zhang et al., 2021). However, there is limited research on how the DE impact on factor marketization influences the regional TFP gap. The only research shows that knowledge spillover promotes the rationalization and advancement of human capital, thereby improving TFP (Hattori et al., 2021). Compared with this article's conclusion, the mechanism's exploration is still incomplete. Based on the mechanism discussed in this article, empirical findings indicate that the digital economy contributes to the market-oriented flow of factors in regional and industry synergies, thereby narrowing the regional TFP gap.

Table 7. Testing the adjustment mechanism – factor marketization

Variables	Factor marketization (*MARKE*)		Regional TFP gap (*GAP_TFP*)	
	(1)	(2)	(3)	(4)
DEI	0.0377*** (0.007)	0.0438*** (0.009)	0.204** (0.094)	0.207** (0.092)
DEI^2	—	—	–0.207 (0.248)	–0.218 (0.262)
MARKE	—	—	–0.168** (0.076)	–0.179*** (0.0840)
MARKE×*DE*I	—	—	0.261*** (0.084)	0.249* (0.134)
$MARKE \times DEI^2$	—	—	–0.242** (0.121)	–0.301** (0.137)
Individual fixed effects	Fixed	Fixed	Fixed	Fixed
Time fixed effects	Fixed	Fixed	Fixed	Fixed
R^2	0.279	0.282	0.178	0.171

Note: Values in parentheses are standard errors; "*", "**",and "***" represent significant at 10%, 5%, and 1% significance levels, respectively.

5.2. Testing the adjustment mechanism – resource misallocation

Table 8 shows the results of examining the resource misallocation adjustment mechanisms. In Panel A, you can find the test results for the capital misallocation adjustment mechanism, with columns (1) to (4) representing the results of heterogeneous tests for the entire country and the eastern, central, and western regions. Meanwhile, Panel B contains the test results for the labor misallocation adjustment mechanism, with columns (5) to (8) representing the results of heterogeneous tests for the entire country and the eastern, central, and western regions. These results provide insights into the following.

We focus on the nonlinear characteristics and regional heterogeneity of the effects of DE on the regional TFP gap from the perspective of resource misallocation.

The results from Panel A's examination of the moderating effects of capital misallocation show that the coefficient for the interaction term between capital misallocation and the digital economy development (DE) index is 0.299, with significance at the 1% level. Similarly, the coefficient for the squared interaction term is –0.286, also showing significance at the 1% level. These findings demonstrate that, when viewed through the lens of capital misallocation, there is a nonlinear "inverted U-shaped" association between the digital economy and the regional TFP gap. The inflection point of this curve is 0.52, which differs significantly from the baseline regression's inflection point of 0.67. This difference suggests that reducing capital misallocation significantly strengthens the digital economy's ability to narrow the regional TFP gap, enhancing its balancing and coordinating effect, thereby partially confirming Hypothesis 3.

Furthermore, heterogeneity tests indicate that the improvement of capital misallocation significantly enhances the DE impact in narrowing the regional TFP gap. However, this effect is significant only in the eastern region. This implies that the eastern region mainly reduces the regional TFP gap by allocating more capital to regions with lower TFP. Similar to the discussion above, results from Panel B, examining the moderating effects of labor misallocation, show that from the perspective of labor misallocation, there is an "inverted U-shaped" nonlinear effect between the DE and the regional TFP gap. The inflection point of this "inverted U-shaped" curve is 0.48, significantly different from the baseline regression's inflection point of 0.67. This suggests that improving labor misallocation significantly strengthens the digital economy's ability to reduce the regional TFP gap, thereby enhancing its balancing and coordinating effects. However, the results of the heterogeneity test differ from previous findings. The enhancement effect of labor misallocation on the contribution of the digital economy to narrowing the regional TFP gap is significant only in the central and western regions, particularly in the western region. This indicates that in these areas, the digital economy primarily reduces the regional TFP gap by altering the employment structure and enabling the movement of surplus labor to regions with higher TFP.

The above findings indicate that the digital economy profoundly impacts the way and efficiency of market factor allocation. However, there is no comprehensive investigation addressing the mechanism by which the digital economy influences the factor allocation TFP gap. Existing literature has only focused on the correlation between the digital economy and factor allocation for simple discussion (Evans & Price, 2020). The above empirical results show that the mechanism for improving resource mismatch varies in different regions with different levels of TFP. We analyze the reasons from the perspectives of labor and capital allocation.

Table 8. Adjustment mechanism test: resource misallocation

Panel A: level of capital mismatch				
Variables	Nationwide (1)	Eastern (2)	Central (3)	Western (4)
DEI	0.220*** (0.051)	0.255** (0.115)	0.021** (0.009)	0.017 (0.088)
DEI^2	–0.177** (0.085)	–0.187*** (0.049)	–0.148** (0.067)	–0.168* (0.096)
MISMATCH	–0.164** (0.071)	–0.184*** (0.057)	–0.144** (0.072)	–0.157* (0.087)
MISMATCH×DEI	0.299*** (0.055)	0.274** (0.127)	0.218 (0.286)	0.225** (0.104)
$MISMATCH \times DEI^2$	–0.286*** (0.044)	–0.297** (0.136)	–0.251* (0.138)	–0.237 (0.384)
Individual fixed effects	Fixed	Fixed	Fixed	Fixed
Time fixed effects	Fixed	Fixed	Fixed	Fixed
R^2	0.177	0.192	0.192	0.180
Panel B: level of labor mismatch				
Variables	Nationwide (5)	Eastern (6)	Central (7)	Western (8)
DEI	0.210** (0.096)	0.201** (0.093)	0.022* (0.014)	0.019* (0.012)
DEI^2	–0.163*** (0.061)	–0.137*** (0.052)	–0.191*** (0.072)	–0.155** (0.070)
mis L	–0.164** (0.078)	–0.184*** (0.057)	–0.144** (0.068)	–0.157* (0.071)
mis L×DEI	0.283*** (0.060)	0.257* (0.149)	0.293** (0.135)	0.277** (0126)
$mis\ L \times DEI^2$	–0.290** (0.137)	–0.217 (0.183)	–0.244* (0.137)	–0.311*** (0.041)
Individual fixed effects	Fixed	Fixed	Fixed	Fixed
Time fixed effects	Fixed	Fixed	Fixed	Fixed
R^2	0.201	0.222	0.221	0.197

Note: Values in parentheses are standard errors; "*","**",and "***" represent significant at 10%, 5%, and 1% significance levels, respectively.

Firstly, in the current situation of low TFP and excessive surplus labor in the central and western regions of China, while the overall quality of TFP and labor in the eastern regions is relatively high, the digital economy promotes the agglomeration of surplus labor in the eastern regions by changing the industrial structure of surplus labor, especially in rural areas, and enriching employment channels. Meanwhile, it weakens the impact of labor allocation improvement on the TFP gap in the eastern regions. Meanwhile, the outflow of surplus labor, the return of high-quality and highly skilled employment personnel in the eastern regions, and the improvement of urbanization levels in the central and western regions can also improve their TFP level (Pan & Lai, 2019). Secondly, from the perspective of optimizing capital allocation, the digital economy's development only significantly narrows the regional TFP gap in the eastern region. The reason may be that, on the one hand, the capital in the eastern region has a first-mover advantage compared to the central and western regions, and the digital economy can improve the accessibility of capital in areas with low TFP. On the other hand, for areas with low TFP levels in the eastern region, especially in rural areas dominated by an agricultural economy, optimizing capital allocation effectively enhances urban capital return and improves urban-rural capital mismatch (Pan & Lai, 2019). Meanwhile, relevant literature indicates a strong causal relationship between human capital level and agricultural TFP (Fuglie et al., 2021; Gillman, 2021). Therefore, relative to the central and western regions, the eastern region has the prerequisite to improve the agricultural TFP gap due to its comparative advantages in capital level and human resources. Therefore, from the perspective of capital allocation optimization, the development of the digital economy only contributes significantly to narrowing the regional TFP gap in the eastern region.

6. Conclusions and recommendations

6.1. Conclusions

We take the regional TFP gap as the main research object, focusing on the impact and mechanism of DE on it. Based on the serious regional imbalance in the development of China's digital economy and the widening digital divide, we focus on examining the dynamic influence and mechanism of transmission of China's DE on the gap in urban TFP from the perspective of factor marketization and resource mismatch. The main achievements are as follows:

If we take the entire period from 2010 to 2022 as the research object, the DE not only fails to narrow the regional TFP gap but also significantly expands the regional gap to a certain extent. In addition, there is a marked "inverted U-shaped" correlation between the two. However, it does not help to narrow the regional TFP gap in the early stage of DE, manifested as the "Digital Divide". However, in the middle and later stages of DE, it significantly inhibits the regional TFP gap, manifested as "Digital Divide". This result is still robust after considering spatial effects.

② The impact of DE on regional TFP gaps varies with the degree of these gaps. Digital economic development reduces TFP gaps only in the regions with the most significant disparities (comprising 20% of the total sample). It has no such effect in most other regions (accounting for 80% of the total sample).

③ The level of factor marketization significantly enhances the role of DE in reducing regional TFP gaps. Resource misallocation improvement also plays a similar role, but the improvement paths differ across regions with varying TFP levels. Specifically, the improvement in capital misallocation significantly enhances the reduction of regional TFP gaps only in the eastern regions. In contrast, labor misallocation improvement is significant in the central and western regions, particularly in the western regions.

6.2. Recommendations

Continue to promote the coordinated DE, remove barriers in factor flow, and assist in crossing the "U-shaped" turning point of the digital economy and regional TFP gap. It is essential to persist in implementing the national integration process of the modern digital economic system and to deepen the regional integration strategic layout of the digital economy, such as "Broadband China," "Digital China," and "East Calculations, West Data." Use these opportunities to accelerate the construction of comprehensive digital service projects, including nationwide 5G networks and next-generation internet infrastructure, to facilitate the flow of information and data and thus clear the path for regional economic coordination. Simultaneously, each region should determine its position in the overall development of the national digital economy and make full use of national, regional complementary, and cooperative policies to advance regional development. Finally, guide tilted funding from "data-rich regions" to "data-poor regions," coordinate Din urban and rural areas, the eastern and western regions, facilitate the two-way flow of new factors, including information and data, across regions, remove barriers to factor flow, and assist in crossing the "U-shaped" turning point of the digital economy and regional TFP gap.

② Strive to optimize resource allocation and actively guide the orderly and smooth flow of various factor resources. Top-level institutional design is the key to optimizing the rational allocation of digital economic factor resources. It is necessary to effectively utilize government policy guidance and top-level institutional design functions. While strengthening the infrastructure of the digital economy, there is a need to foster the development of the Internet and its related industries in the central and western regions and guide innovative talent and capital to flow into the core digital economy industrial chains in the central and western regions through various means, such as internet innovation and entrepreneurship bases and high-tech industrial parks. At the same time, actively explore factor marketization reforms to guide the orderly flow of labor across regions, continually bridge the labor market mobility barriers, and enhance the efficiency of labor factor market allocation Finally, narrowing the regional TFP gap is a complex and systematic endeavor. It is necessary to gradually tilt digital service public resources to the central and western regions, explore methods to remove mobility barriers for factors such as labor and capital among regions and between urban and rural areas during the process of improving digital service quality, and actively release the digital economic potential in the central and western regions through both external introduction and internal activation. This will help restructure the interaction order of regional factors and explore new paths for improving TFP in the central and western regions under the impetus of the digital economy.

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