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To cite this article: Yanling Li, Mengxin Wang, Gaoke Liao & Ran Gu (2023) The impact of digital finance on energy total factor productivity, Economic Research-Ekonomiska Istraživanja, 36:3, 2263535, DOI: [10.1080/1331677X.2023.2263535](https://doi.org/10.1080/1331677X.2023.2263535)

To link to this article: <https://doi.org/10.1080/1331677X.2023.2263535>



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Published online: 30 Oct 2023.



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The impact of digital finance on energy total factor productivity

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ABSTRACT

In the context of modern scientific and technological revolution and industrial transformation, the development of digital finance is conducive to improving the ecological environment and the energy total factor productivity (TFP). In this paper, DEA cross-efficiency model is used to measure the energy TFP, and moment estimation method is used to empirically test the influence and heterogeneity of digital finance on energy TFP, and then the intermediary model is constructed to study and analyze the influence mechanism based on the sample data of 30 provinces in the Chinese Mainland from 2011 to 2018. The following research findings are obtained. First, the development of digital finance has played a significant role in improving energy TFP. Second, spatial heterogeneity exists in the process of digital finance affecting energy TFP improvement, that is, digital finance has a more obvious improvement effect on the energy TFP in central and western China than in eastern China. Third, digital finance can affect energy TFP through technological innovation; that is, the improvement of regional technological innovation is an important transmission mechanism for digital finance to affect energy TFP.

ARTICLE HISTORY

Received 13 June 2022

Accepted 18 September 2023

KEYWORDS

Digital finance; energy total factor productivity; technological progress; mediating effect

JEL CLASSIFICATIONS

C51; O13; O35

1. Introduction

1.1. Motivation

With the rapid economic growth, the extensive growth mode with high investment, high energy consumption and high pollution gradually shows its drawbacks, which not only wastes resources and causes energy shortage but also damages the ecological environment and affects human health. At this stage, the process of urbanization and industrialization in China is still advancing continuously, and the rapidly increasing and rigid energy demand leads to the increasingly fierce contradiction between energy supply and demand, restricting economic growth to a certain extent. An important

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way to achieve sustainable economic growth and ecological environment stability is energy conservation and emission reduction, which puts forward higher requirements for energy development and utilization. Under the existing constraints of energy resources, it is an important way to improve the energy TFP to meet the needs of the coordinated development of ecological environment and economic growth.

1.2. Literature review and contribution

At present, green development is still the core of the coordinated economic development environment, and a large number of studies have emerged on the influencing factors of energy TFP. Economic development is the goal and foundation, in this development process to environmental protection put forward higher requirements, so the coordination of economic environment development is another important goal of development. Environmental pollution accompanied by economic development is often inevitable, but financial factors can promote the improvement of technical efficiency and the optimization and upgrading of industrial structure, so as to reduce carbon emissions by improving the technological level (Huang et al., 2022; S. Liu et al., 2021; Yao et al., 2021). At the same time, energy price, energy structure and regional energy endowment also affect the improvement of energy TFP to a certain extent (Li et al., 2018; Sha et al., 2022). Other studies consider the impact of government intervention on energy TFP from the perspective of government intervention (Chiou et al., 2011; Fu, 2018). Technological innovation and innovation activity aimed at saving production costs are the key to improving energy TFP (Cagno et al., 2015; Ramirez-Portilla et al., 2014). Although many studies have studied and analyzed the energy TFP, with the advent of the digital era, the research of energy TFP still needs to be further expanded.

With the development of The Times, the academic circle has carried out research on digital finance and energy TFP. Financial development is not a barbaric development mode at the cost of environment, but through promoting technological innovation to optimize industrial structure and ultimately promote economic growth (Hsu et al., 2014; Jalil & Feridun, 2011). Through transnational studies, it has been proved that there is a direct relationship between financial development and energy consumption (Cheng & Qu, 2020). Energy consumption growth is positively affected by financial development and there is a long-term equilibrium relationship between the two. Under the background of digitalization, financial deepening and capital deepening work together. Digital finance provides financial support for the development and utilization of new technologies of enterprises through financial means such as credit support, and improves energy TFP by effectively reducing energy consumption (Islam et al., 2013; Sadorsky, 2011). Cagno et al. (2015) and Ramirez-Portilla et al. (2014) believe that digital finance promotes technology spillover in energy production, transportation, storage, consumption and other processes through the technical association and interaction between the network and operation departments, which is conducive to promoting the diffusion of energy utilization efficiency. Herrerias et al. (2016) further found that digital finance promotes capital accumulation and collaborative R&D cooperation of innovation subjects, and forms technology spillover through the flow

of resources, talents, capital and other factors. Digital finance not only provides a channel for innovation, but also further uses the effect of technology upgrading to promote R&D innovation and efficient use of energy in the corporate sector, which is conducive to reducing costs and promoting low-carbon development of regional economies (Lv et al., 2021; Tsou & Chen, 2023).

Through literature review, it is found that existing studies mainly focus on the influencing factors of energy TFP, which provides inspiration for the exploration of the path of energy TFP improvement in this paper. However, the research on the impact of digital finance on energy TFP is insufficient. The existing literature focuses on the marginal benefits brought by technological innovation factors, and under the background of digitalization, the digital technology characteristics of digital finance may have a greater enhancement effect on energy TFP. This paper studies the impact of digital finance on energy TFP, focuses on the environmental effects of digital finance in the context of low-carbon economic development, and focuses on the impact degree and mechanism of digital finance on energy TFP. Its marginal contribution is mainly as follows: First, it studies whether digital finance will play a role in energy TFP. By combining dynamic and static methods, the direction and degree of the effect of digital finance development on energy TFP are fully investigated. Second, from the perspective of spatial heterogeneity, this paper studies whether the increase of energy TFP under location factors reflects the impact of heterogeneity. Thirdly, from the perspective of the intermediary effect of technological innovation, this paper studies the influence of technological innovation mechanism on the improvement of energy TFP.

The rest of this paper is arranged as follows: The second part is theoretical analysis and research hypothesis, including the impact and mechanism analysis of digital finance on energy TFP, and put forward the research hypothesis. The third part is the research method design, including static and dynamic panel data model and mediation effect model construction, and the measure of energy TFP. The fourth part is variable selection and data sources, explaining the reasons and sources of variable selection. The fifth part is the empirical results and analysis. The sixth part is the basic conclusion.

2. Theoretical analysis and research hypothesis

2.1. The promoting effect of digital finance on energy TFP

The development of the financial effect of digital finance promotes the improvement of the overall factor of energy. To improve the stability of ecological environment and energy TFP requires not only the formulation of reasonable policies for supervision, but also the rational allocation of financial resources by playing the role of finance. Sustained and stable financial support promotes innovative activities to further improve energy TFP and achieve high-quality economic growth. Under the development of traditional finance, funds tend to flow into high-polluting enterprises with high assets (Islam et al., 2013). Digital finance promotes the financing efficiency of enterprises by expanding financing channels, satisfies the supply of capital elements in the innovation process of enterprises, and has a significant positive impact on the

digital transformation and innovation development of enterprises (T. Li et al., 2022; X. J. Liu et al., 2021). The financial system plays its function of optimizing resource allocation, enabling high-tech industries and a series of industries with the output target of green economy to have a better financing environment, and improving the utilization efficiency of capital and other production factors.

The technological effects of digital finance promote the improvement of energy TFP. As far as the development of digital finance itself is concerned, the financial means of obtaining information by using the characteristics of the Internet can effectively avoid the misallocation of financial resources. Digital finance with innovative financial models organically combines traditional finance with technological innovation and big data, diversifies financial products, service objects and financing methods, and gradually improves financial scale and efficiency, which is conducive to improving the mismatch of financial resources and solving financing constraints. Digital finance promotes the progress of financial models through digital technology, broadens the malleability of innovation, and technological innovation can gain advantages in production methods. It can promote the greening of resource exploitation and energy utilization, and achieve low carbon waste emissions.

The network effects of digital finance can improve energy TFP. The network characteristics of digital finance determine that it has more perfect information in the process of providing financial services, improving the symmetry of information and the efficiency of financial capital allocation. The network effect of digital finance enables information sharing, and the disclosure of green products and environmental protection information enhances the sense of corporate responsibility (Su et al., 2021), breaks the original barriers of information asymmetry, and enables labor, capital, technology and other production factors to achieve cross-regional joint effect, promoting the improvement of energy TFP. Therefore, the first hypothesis is proposed.

Hypothesis 1: Digital finance can promote the improvement of energy TFP.

2.2. Heterogeneous analysis of the impact of digital finance on energy TFP

There are differences in regional financial development, including the differences in the development of financial sectors among regions, differences in financial systems, and differences in economic development (di Pietro et al., 2019; Palacin-Sanchez & Di Pietro, 2016). Differences in regional financial development exist in the geographic space and the economic space. Financial distribution, structure, and development are often closely related to regional economic growth. Although there is a knowledge spillover effect between regions, due to the differences in the thinking and professional training of financial practitioners in various regions, the development degree of financial system in each region is different, and finally, the regional financial heterogeneity is formed.

The spatial distribution of financial resources is highly heterogeneous in the Chinese Mainland, and financial resources are mainly concentrated in the eastern coastal region. Regional economic growth is closely related, and the uneven distribution of financial resources makes regional development different (T. Li et al., 2021; Li & Ma, 2021; Liu et al., 2020). Although the network characteristics of digital finance

promote information sharing, factors such as regional loss and regional differences may cause information loss in the process of spatial transmission. There is a considerable gap between the development pace of China's eastern, central and western regions. On the one hand, the central and western regions have fewer factors of production, such as capital and labor, while the eastern regions have advantages in terms of geographical location and transportation conditions. On the other hand, there is also a gap in the original accumulation of financial resources and scientific and technological resources between the central and western regions and the eastern regions. Therefore, the second hypothesis is proposed.

Hypothesis 2: Spatial heterogeneity exists in the process of digital finance affecting energy TFP improvement; that is, digital finance has a more obvious improvement effect on the energy TFP in central and western China than in eastern China.

2.3. The mediating effect of digital finance on energy TFP

Digital finance promotes technological innovation and development (M. X. Wang et al., 2021), and the technological progress brought by innovation is an essential driving force to improve energy TFP. Traditional financial development often falls into financial risks due to information asymmetry and high operating costs. With the progress of digital financial technology and information technology, digital payment means, lending and other diversified financial products are provided to the public, reducing transaction costs and transaction risks. Digital finance provides financial support for technological innovation of enterprises and relieves financing constraints of enterprises, which also provides opportunities for technological progress of enterprises. In addition, the data processing capability of digital finance, fintech and financial supervision are conducive to the innovation and efficiency of enterprises, so as to effectively utilize the financial resources of the market (Cheng & Qu, 2020; Gomber et al., 2018; Huang et al., 2019; Z. Li et al., 2022). Financial development promotes the rational allocation of financial resources, significantly promotes the transformation efficiency of savings and investment, and promotes the technological progress of enterprises through the effective allocation of funds.

R&D investment can effectively stimulate enterprise technological innovation, which is a key factor to improve energy TFP (Chiou et al., 2011; W. C. Li et al., 2021; Zhu et al., 2021). First of all, the improvement of technological level reduces the difficulty of energy exploitation and production cost, thereby improving the energy supply capacity. Meanwhile, the application of new technologies is conducive to promoting the research and development of new energy, developing and utilizing more abundant renewable energy and clean energy, maintaining high utilization efficiency and low pollution emission in the process of energy use, promoting the improvement of productivity and the development of green economy. Secondly, technological innovation means the optimization and upgrading of industrial structure, which is conducive to improving the utilization efficiency of energy (X. Y. Wang et al., 2021). With the adjustment of industrial structure, high-intensity energy-consuming industries naturally reduce their proportion. Based on the above analysis, technological innovation mainly relies on the expansion of energy supply and the reduction of energy consumption to provide support for the improvement of energy

TFP, and ultimately promote economic growth through high output level. Therefore, the third hypothesis is proposed.

Hypothesis 3: Technological innovation plays an intermediary role in the process of digital finance promoting energy TFP, and digital finance promotes the improvement of energy TFP by improving the level of technological innovation.

3. Research methods

3.1. Static panel data model

In order to empirically analyze the impact of digital finance on energy TFP, this paper sets up a static panel data model, and the specific expression is as follows:

$$EE_{i,t} = \beta_1 DIF_{i,t} + \beta X_{i,t} + \mu_i + \varepsilon_{i,t} \quad (1)$$

In Formula (1), EE is the explained variable energy TFP; DIF is the explanatory variable digital finance; X represents a series of control variables selected in this study; i stands for the sample province; t is the time; μ is the individual effect, and ε is the random disturbance term.

3.2. Dynamic panel data model

The static panel data model considers the impact of digital finance development in different regions on energy TFP in the current period, but it does not investigate the dynamic impact, that is, the impact of previous energy TFP on current energy TFP. Energy TFP is a dynamic and gradual process with development inertia. It is not in line with the actual situation of energy TFP if we only consider the influence of current digital finance. In this paper, a one-period lag of energy TFP is added to the static panel data model as the explanatory variable to obtain the dynamic panel data model. The expression of the dynamic panel data model is as follows:

$$EE_{i,t} = \alpha EE_{i,t-1} + \beta_1 DIF_{i,t} + \beta X_{i,t} + \mu_i + \varepsilon_{i,t} \quad (2)$$

In Formula (2), $EE_{i,t-1}$ refers to the energy TFP of province i in period $t-1$, and the meanings of other variables are the same as those in Formula (1).

3.3. Mediating effect test model

This paper adopts the mediating effect test method to explore the direct effect of digital finance on energy TFP, and whether digital finance will produce a mediating effect through the mediating variable: technological innovation. Meanwhile, the degree of the mediating effect is also measured. The expression for constructing the mediating effect model is as follows:

$$EE_{i,t} = \theta_1 + \alpha DIF_{i,t} + \sum_{k=1}^3 \beta_{1k} CONTR_{ikt} + \varepsilon_1 \quad (3)$$

$$INN_{it} = \theta_2 + \delta GTI_{it} + \sum_{k=1}^3 \beta_{2k} CONTR_{ikt} + \varepsilon_2 \quad (4)$$

$$EE_{it} = \theta_3 + \alpha' GTI_{it} + \gamma INN_{it} + \sum_{k=1}^3 \beta_{3k} CONTR_{ikt} + \varepsilon_3 \quad (5)$$

In Formulas (3), (4) and (5), $EE_{i,t}$ represents the energy TFP; $DIF_{i,t}$ represents digital finance; INN_{it} stands for technological innovation, which is the mediating variable; $CONTR_{ikt}$ represents a series of control variables, the subscripts i , t and k represent sample province, time and control variables, respectively, where $i=1, 2, \dots, 31$, $t=1, 2, \dots, 9$, $k=1, 2, 3$; ε is the random error term.

3.4. Measurement of energy TFP

The measurement of energy TFP is roughly divided into two categories. The first is to use a single indicator to characterize energy utilization efficiency, including energy intensity, energy productivity, and energy technological efficiency (Adom & Kwakwa, 2014). The second is the efficiency TFP considering multiple inputs and multiple outputs (Filippini & Hunt, 2015; Zhou et al., 2012). Compared with simple and intuitive single-factor energy efficiency indicators, total-factor energy efficiency considers the combination of energy, labor, capital and other endogenous growth factors to explain the impact of energy endowment on energy efficiency (Hu & Wang, 2006). With the increasingly exposed contradiction between ecological environment and economic growth, some studies incorporate environmental factors as input factors into the energy TFP measurement framework.

The Data Envelopment Analysis (DEA) method can examine the dynamic changes of the energy TFP. The traditional DEA method is only based on self-assessment, which cannot effectively realize the full ranking of decision-making units, resulting in a lack of comparability between decision-making units. Based on the extension of the traditional DEA, the DEA cross-efficiency model can help explore the changes of energy TFP by considering the self- and other evaluation, so that the evaluation results of the decision-making units are fair and comparable. The basic form of the DEA cross-efficiency model is as follows:

Set s as the number of provinces selected in this paper. the vectors of energy input indicator m and energy output indicator n of DMU_i are expressed as: $X_i = (x_{1i}, x_{2i}, \dots, x_{mi})^T > 0$, $Y_i = (y_{1i}, y_{2i}, \dots, y_{ni})^T > 0$, $1 \leq i \leq s$.

$$\hat{\theta}_{di} = \text{Max} \sum_{r=1}^n u_{rd} y_{rd} \quad (6)$$

$$\sum_{j=1}^m \mu_{jd} x_{ji} - \sum_{j=1}^m u_{jd} y_{ji} \geq 0 \quad (7)$$

$$\sum_{j=1}^m \mu_{jd} x_{jd} = 1 \quad (8)$$

$$\sum_{j=1}^m \mu_{jd} x_{jd} - \theta_d \sum_{j=1}^m u_{jd} y_{jd} = 0 \quad (9)$$

$$\mu_{jd} \geq 0, j = 1, 2, \dots, m \quad (10)$$

$$u_{jd} \geq 0, j = 1, 2, \dots, n \quad (11)$$

In Formula (6), $\hat{\theta}_{di}$ represents the cross-efficiency value of DMU_i $1 \leq i \leq s$ based on DMU_d ; the final energy TFP value of DMU_i is represented by the average value of the cross-efficiency values obtained by DMU_d from DMU_1 to DMU_s .

4. Variable selection and data source

This paper takes energy TFP as the explained variable, which is measured in sub-Section 3.4. In the calculation of energy TFP, the input and output of means of production are mainly considered. This paper also focuses on the expected and unexpected outputs. For Input indicators, this paper mainly selects labor, capital stock and energy consumption. This paper takes urban employment to represent the labor input. Capital stock is estimated by the perpetual inventory method used in previous literature (Zhang, 2008). The basic equation is $K_{i,T} = K_{i,T-1}(1 - \delta_{i,T}) + I_{i,T}$ where i and T represent province i and period T , respectively; δ is the economic depreciation rate; I is the total fixed capital formation. The initial capital stock is obtained by dividing the fixed capital in the initial year by 10%, and the economic depreciation rate δ is set to 9.6%. Energy consumption is represented by the total energy consumption of each province. Expected output and undesired output are GDP and carbon dioxide emissions, respectively, and the GDP of each province is deflated to the actual gross regional product with 2000 as the base period. Referring to previous research (Li et al., 2019), this paper estimates the carbon dioxide emissions with the formula $CO_{2i} = \sigma_c V_c + \sigma_o V_o + \sigma_q V_q$, where V_c , V_o , and V_q represents the energy consumption of coal, oil and natural gas required for production in province i , respectively; σ_c , σ_o , and σ_q represents the carbon emission coefficient of coal, oil and natural gas, respectively. The description of the input-output variables of energy TFP measurement is shown in Table 1.

The explanatory variable of this research is digital finance, which is characterized by the digital financial inclusion index compiled by the Institute of Digital Finance, Peking University. According to the existing literature, the Digital Financial Inclusion Index includes three dimensions, including the coverage of digital finance, the depth

Table 1. Energy TFP measurement indicators.

	Variable	Measurement	Source	Unit
Input variable	Labor input	Urban employment	Statistical yearbooks of all provinces	Thousands of people
	Capital input	Perpetual inventory method	Wind database	100 million
	Energy input	Total energy consumed	EPS database	Ten thousand tons of coal
Output variable	Expected output	Regional GDP	State Statistical Bureau	100 million yuan
	Undesired output	Carbon dioxide emissions	EPS database	Ton

Source: Author collated.

of use of digital finance and the digitization degree of inclusive finance, reflecting the penetration of digital and mobile financial services into remote areas. It mainly follows three principles: taking both breadth and depth into account; considering both vertical and horizontal comparability; reflecting the multilevel and diversity of financial services. Therefore, the Digital Financial Inclusion Index is comparable and can well reflect the development of digital finance.

Technological innovation is selected as the intermediary variable, and the number of patent applications accepted in each province is used to measure the regional technological innovation level in this paper.

Referring to relevant literature, this paper selects foreign direct investment (FDI), industrial structure optimization and government financial investment as control variables. First, the impact of foreign direct investment on the energy TFP is twofold. On the one hand, the influx of foreign investment injects vitality into the development of enterprises, while the excessive pursuit of development speed and the neglect of development quality aggravate the local environmental pressure. On the other hand, the concentration of talents and industries brought by foreign enterprises can effectively improve energy efficiency. This paper selects the proportion of FDI in GDP converted by the average exchange rate of the corresponding year as the measurement variable. Second, the upgrading of industrial structure mainly influences the energy TFP by optimizing the industrial structure. When the industrial structure is optimized and upgraded, regional industries will be led to change from the inefficient and energy-intensive industrial structure to the high-output and energy-intensive industrial structure. This paper selects the ratio of the added value of the tertiary industry to the added value of the secondary industry to measure the optimization efficiency of the regional industrial structure. Third, government financial investment plays a certain role in the allocation of market resources, thus affecting energy TFP. This paper selects the proportion of government financial expenditure in regional GDP to measure the intensity of government financial investment. The main variables selected in this paper are described in Table 2.

In view of the lack of relevant data in Hong Kong, Macao, Taiwan and Tibet, these provinces are not included in this analysis. According to the statistical yearbooks and other data records of various provinces, the capital investment data used to measure the energy TFP is temporarily updated to 2018. The digital financial inclusion index published by the Institute of Digital Finance, Peking University, started in 2011, because

Table 2. Core variables and control variables.

	Variable	Symbol	Unit	Measurement
Explained variable	energy TFP	EE	/	The DEA cross-efficiency model
Explanatory variable	digital finance	DIF	/	Peking University Digital Financial Inclusion Index
Mediating variable	technical innovation	INN	Ten thousand pieces	Number of patent applications accepted
Control variable	foreign direct investment	FI	%	The proportion of foreign direct investment in regional GDP
	industrial structure optimization	IS	%	The ratio of the added value of the tertiary industry to that of the secondary industry
	government financial investment	GOV	%	the proportion fiscal expenditure in regional GDP

Source: Author collated.

before 2011, the statistical indicators required to construct the digital financial inclusion index are not comprehensive. In addition, the statistics of capital input factors required to calculate the energy TFP have a time lag. This paper finally selects 30 provincial panel data in the Chinese Mainland from 2011 to 2018 as the sample of empirical research, with 240 observed values for each variable. The data related to digital finance comes from the Digital Financial Inclusion Index published by the Institute of Digital Finance, Peking University. The original data for measuring energy TFP and other variables come from the EPS database, the Wind database, the National Bureau of Statistics, China Statistical Yearbooks, Statistical Yearbooks and Statistical Bulletins of various provinces.

5. Results and discussion

Before ordinary panel regression, a multicollinearity test was conducted on the variables, and the results were shown in Table 3.

The variance inflation factors of all variables are less than 10, indicating no multicollinearity problem. So the following regression analysis can be performed.

5.1. Benchmark regression results

First, Hausman test was conducted, and the test result (p value less than 0.1) indicated that the fixed-effect model was more accurate for regression results. This paper uses the ordinary least squares estimation (OLS) and the fixed effect model (FE) to test the impact of digital finance on energy TFP. The estimated results are shown in Table 4.

Table 3. Variance inflation factor regression results.

Variable	VIF	1/VIF
DIF	1.21	0.83
INN	1.26	0.79
FI	1.31	0.76
IS	1.15	0.87
GOV	1.02	0.98
Mean VIF	1.19	

Source: Author-created through Stata software.

Table 4. Benchmark regression.

	EE	
	OLS	FE
DIF	0.5467*** (0.0870)	0.2433*** (0.0719)
IS	-0.0205 (0.0163)	0.191*** (0.0366)
FDI	1.278* (0.653)	0.0204 (0.799)
GOV	-0.0131 (0.0131)	-0.0260 (0.0701)
_cons	0.921*** (0.0306)	0.793*** (0.0463)
Individual effect	Control	Control
N	240	240
R^2	0.151	0.385

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author-created through Stata software.

The development of digital finance has significantly boosted the energy TFP. According to the OLS and the FE estimation of the static panel data model, the regression coefficients of digital finance are 0.5467 and 0.2433, respectively, which are significant at the 1% level, indicating that digital finance has a significant positive impact on energy TFP. Hypothesis 1 is verified. Firstly, digital technologies represented by artificial intelligence penetrate all walks of life, promoting the process of industrial digitization and industrial structure optimization and upgrading. Through changes in production efficiency, the dependence of economic output on energy use is alleviated; thus, the energy TFP is improved. Secondly, the financial system is continuously improved through digital technology, and it can provide R&D funding support for social scientific and technological innovation activities, thereby improving the pollution discharge efficiency.

Among the control variables, the impacts of industrial structure optimization and foreign direct investment on energy TFP are significantly positive. By optimizing and upgrading industrial structure and the technology spillover caused by talent agglomeration brought by foreign-funded enterprises, regional energy utilization efficiency is improved. The impact of government financial investment on energy TFP is not significant. There may be government intervention behavior that local governments tend to choose high-yield industries, which hinders the effect of market resource allocation.

To further study from a dynamic perspective, this paper uses a dynamic panel data model to conduct an empirical analysis of the relationship between digital finance and energy TFP. The first differenced GMM estimation (DIF-GMM) and the system GMM estimation (SYS-GMM) are used to estimate the model to eliminate the endogeneity problem, and the robustness of the estimation results was verified. The *p* value of the AR(1) test of each model is less than 0.1 and the *p* value of the AR(2) test is greater than 0.1, indicating that there is no second-order positive correlation. The *p* value of the Hansen test is greater than 0.1, indicating that there is no over-identification problem. The model setting is reasonable and effective. See Table 5 for the results.

Table 5. GMM estimation results.

	Energy TFP	
	DIF-GMM	SYS-GMM
LEE	0.834*** (0.0554)	1.049*** (0.0392)
DIF	0.147*** (0.0428)	0.216*** (0.0301)
IS	0.103*** (0.0328)	-0.0019 (0.0097)
FDI	0.230 (0.668)	-0.0276 (0.366)
GOV	-0.0138 (0.0092)	-0.0196 (0.0333)
AR1-p	0.006	0.006
AR2-p	0.282	0.319
Hansen-p	1.000	1.000
N	180	210

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Individual fixed effects are controlled for in all regressions.

Source: Author-created through Stata software.

Digital finance has a significant and sustained positive impact on energy TFP. Through the two estimation methods of DIF-GMM and SYS-GMM, Digital finance can significantly improve energy TFP. Including the one-stage lag variable of energy TFP, the GMM estimation results show that the one-stage lag coefficient of energy TFP is significantly positive, indicating that there is significant time continuity in the process of improving energy TFP, which means that the development of energy TFP in the early stage is likely to guide its subsequent development direction. At the same time, under the concept of ‘ecological priority and green development’, more funds should be poured into the field of technological innovation in economic development, thereby promoting the improvement of energy TFP through technological innovation.

5.2. Spatial heterogeneity analysis

Due to the differences in digital finance development and economic development level in various regions, there are significant regional differences in the development direction and promotion of energy TFP in different regions. China’s wide land area leads to a sizeable East-West span. The eastern coastal region has surpassed the central and western regions in many indicators such as industrial structure, technological level and economic development due to its convenient transportation conditions and the industrial foundation since the reform and opening up. In order to investigate the heterogeneous impact of digital finance on energy TFP in different regions, based on the difference of regional resource endowment, the 30 sample provinces of the study are divided into the eastern and the central and western regions, which are estimated by the DIF-GMM and the SYS-GMM. See Table 6 for the results. Among them, according to the division of the National Bureau of Statistics, the eastern region includes 11 provinces and municipalities, namely, Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central and western region includes 19 provinces and autonomous regions, i.e., Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi,

Table 6. Spatial heterogeneity regression results.

	The eastern region		The central and western region	
	DIF-GMM	SYS-GMM	DIF-GMM	SYS-GMM
L.EE	0.912*** (0.0550)	1.059*** (0.0741)	0.906*** (0.0583)	1.085*** (0.0997)
DIF	0.1115 (0.0747)	0.088* (0.0530)	0.201*** (0.0490)	0.217*** (0.0517)
IS	0.00207 (0.0196)	0.0723 (0.0616)	0.0907*** (0.0345)	0.0401 (0.0386)
FDI	-0.743 (0.628)	1.563 (1.325)	-0.586 (1.235)	0.496 (0.855)
GOV	0.316 (0.413)	-0.536 (0.567)	-0.0120* (0.00637)	-0.0428 (0.101)
AR1-p	0.039	0.046	0.023	0.023
AR2-p	0.101	0.120	0.743	0.534
Hansen-p	1.000	0.984	1.000	1.000
N	66	77	114	133

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author-created through Stata software.

Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang.

There is spatial heterogeneity in the impact of digital finance on energy TFP, that is, digital finance has a more significant effect on energy TFP in the central and western regions than in the eastern regions. As can be seen from Table 6, digital finance in different regions has room for development, and has a significant positive effect on energy TFP, but the difference lies in the spatial difference in the intensity of improvement. Empirical results show that the improvement effect in the central and western regions is significantly stronger than that in the eastern region, so hypothesis 2 is verified. The reason may lie in the difference in economic and development level between the eastern region and the central and western regions. The eastern region has superior location factors and technical conditions, and has a good development space and economic strength foundation, while the development of the central and western regions mainly relies on labor-intensive industries, and the lagging development pace leads to a gap in the feedback of digital finance among regions. In the eastern region, whether it is the level of technology or financial support, the innovation and development linked by capital has almost reached saturation state, while the technological progress in the central and western regions is still the key goal of development. Therefore, the innovation benefits and influence space of digital finance to the central and western regions are larger.

5.3. Mediating effect estimation results

Based on the panel model test results, which show a significant positive correlation between digital finance and energy TFP, this paper further studies the impact mechanism. The stepwise regression coefficient test method is adopted to explore the impact mechanism of digital finance on energy TFP with technological innovation as the mediating variable. See Table 7 for the results.

Table 7. Test results of the mediating effect of technological innovation.

	(1) EE	(2) INN	(3) EE
DIF	0.243*** (0.0719)	2.573*** (0.221)	0.218*** (0.0748)
IS	0.191*** (0.0366)	0.372*** (0.112)	0.0792*** (0.0272)
FDI	0.0204 (0.799)	3.235 (2.453)	-0.696 (0.733)
GOV	-0.0260 (0.0701)	0.0141 (0.215)	-0.0057 (0.0295)
INN			0.0563*** (0.0142)
_cons	0.793*** (0.0463)	9.403*** (0.142)	0.338** (0.139)
Individual effect	Control	Control	Control
<i>N</i>	240	240	240
<i>R</i> ²	0.385	0.657	0.425

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author-created through Stata software.

Digital finance impacts energy TFP through technological innovation. Column (1) shows that the influence coefficient of digital finance on energy TFP is 0.243 and passes the test at the significance level of 1%, which means that the intermediary effect is possible. (2) reflects that the influence coefficient of digital finance on technological innovation is 2.573, which passes the test at the significance level of 1%, indicating that digital finance has a significant positive impact on technological innovation. In column (3), the influence coefficients of digital finance and technological innovation on energy TFP are 0.218 and 0.0563 respectively, and both pass the significance test. The estimated results show that digital finance and technological innovation have a positive impact on the improvement of energy TFP, and the influence coefficient of digital finance decreases after the addition of technological innovation variables. It shows that technological innovation plays an incomplete intermediary effect in the influence of digital finance on energy TFP, and hypothesis 3 is verified. Digital finance can indirectly promote energy TFP by promoting technological innovation.

The transmission mechanism between digital finance and energy TFP through technological innovation is obvious. On the one hand, the development of digital finance improves the financial system, broadens the scope of financial services, supports the development of innovative activities, uses digital technology to realize the effective allocation of financial resources, alleviates the financing constraints of technologically innovative enterprises, and thus promotes the progress of technological innovation of enterprises. On the other hand, the technological progress of enterprises can improve the production structure, which is conducive to reducing the production cost by reducing energy consumption, and alleviating the pollution emission pressure faced in the production process by using technological advantages, so as to achieve the purpose of improving energy TFP. In general, digital finance can significantly promote technological innovation and promote the improvement of energy TFP through technological innovation.

5.4. Robustness test

According to the estimation results of dynamic and static models, the direction and significance of the estimation coefficients of digital finance on energy TFP are basically the same, which explains the robustness of the estimation results to a certain extent. This paper tests robustness by replacing core explanatory variables, and investigates the impact of digital finance on energy TFP from three sub-dimensions of digital finance inclusion index, including digital finance coverage breadth index (CS), digital finance usage depth index (SD) and digital finance inclusion degree index (DM). All data are from the Peking University Digital Financial Inclusion Index.

According to the robustness test results in [Table 8](#), the lagging coefficient of energy TFP shown in columns (1), (2) and (3) is significantly positive, and the digital finance coverage breadth index (CS), digital finance usage depth index (SD) and digitalization degree index of inclusive finance (DM) have a significantly positive impact on energy TFP. The direction and significance of the estimated coefficients of the three indexes are consistent with the baseline regression, indicating that the estimated results are still robust.

Table 8. Results of robustness test.

	SYS-GMM	energy TFP	
		SYS-GMM	SYS-GMM
L.EE	1.043*** (0.0334)	1.071*** (0.0386)	1.048*** (0.0359)
SC	0.349*** (0.0650)		
SD		0.230*** (0.0766)	
DM			0.341*** (0.0690)
IS	-0.020** (0.0078)	-0.010** (0.0042)	-0.013* (0.0067)
FDI	0.252 (0.541)	-0.220 (0.524)	-0.397 (0.496)
GOV	-0.002 (0.0034)	-0.008 (0.0060)	-0.005 (0.0036)
AR1-p	0.004	0.006	0.005
AR2-p	0.140	0.600	0.280
Hansen-p	1.000	1.000	1.000
N	210	210	210

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author-created through Stata software.

6. Conclusions and policy implications

In the increasingly mature stage of digital technology and informatization, the development of green economy driven by innovation is of great practical significance. Using the panel data of 30 provinces and cities in mainland China from 2011 to 2018, this paper empirically tests the impact of digital finance on energy TFP and its mechanism, and mainly draws the following conclusions.

First, digital finance significantly promotes the improvement of energy TFP. Through the full sample analysis, the panel model was used to verify the positive impact of digital finance on energy TFP from static and dynamic perspectives. Second, digital finance has a spatially heterogeneous impact on the improvement of energy TFP, that is, compared with the eastern region, digital finance has greater marginal benefits on the improvement of energy TFP in the central and western regions. Third, digital finance affects energy TFP through technological innovation, that is, by improving the level of regional technological innovation, digital finance exerts an important transmission mechanism to affect the improvement of energy TFP. As an intermediary factor, technological innovation promotes the improvement of energy efficiency. Improving energy utilization efficiency is the key to achieve energy saving, emission reduction and ecological environment protection, so it is necessary to formulate emission reduction policies reasonably and scientifically.

Based on the above conclusions, this paper obtains the following policy implications: (1) Pay attention to the promotion effect of financial development. Financial development plays a positive guiding role in economic development, industrial structure optimization, energy consumption and pollution discharge. Therefore, while expanding the financial scale, the government should guide the flow of capital, vigorously play the role of financial supervision, and provide financial support for technical innovation projects and companies with development potential. (2) Making

development more inclusive. Due to the unbalanced financial development and differences in regional resource endowments, energy TFP has strong regional characteristics. It is urgent to strengthen the financial system and financial input in the central and western regions, actively promote the transfer of advanced energy-saving technologies to these two regions, and promote the development of clean energy industry. In addition, the central and western regions combined with regional resource advantages to strengthen the construction of technology and innovation, so as to promote the balanced development of regional economy. (3) Promoting major breakthroughs in innovative technologies. Promote the innovation, application and promotion of technology from the actual point of view, improve the production efficiency of enterprises and reduce energy consumption. Use digital technology to avoid information asymmetry, strive for financing opportunities for technology-based potential enterprises, and further provide financial support for innovative entities.

Although this paper expands the research idea of the impact of digital finance on energy TFP, given that the development of energy TFP and digital finance is a continuous process, they are constantly endowed with new connotations along with the changes of The Times, so the measurement methods and indicators of digital finance and energy TFP need to be constantly updated and optimized. In addition, the mechanism analysis part of this paper mainly studies the mechanism role played by the digital technology features of digital finance, while the influence mechanism of more energy TFP improvement paths are worth exploring, such as the network features mechanism of digital finance. Therefore, these aspects will also be one of the contents of the follow-up research in this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research was funded by the Chinese National Funding of Social Sciences, grant number 18ATJ002.

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References

- Adom, P. K., & Kwakwa, P. A. (2014). Effects of changing trade structure and technical characteristics of the manufacturing sector on energy intensity in Ghana [Review]. *Renewable and Sustainable Energy Reviews*, 35, 475–483. <https://doi.org/10.1016/j.rser.2014.04.014>
- Cagno, E., Ramirez-Portilla, A., & Trianni, A. (2015). Linking energy efficiency and innovation practices: Empirical evidence from the foundry sector. *Energy Policy*, 83, 240–256. <https://doi.org/10.1016/j.enpol.2015.02.023>
- Cheng, M., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal*, 63, 101398. <https://doi.org/10.1016/j.pacfin.2020.101398>

- Chiou, T. Y., Chan, H. K., Lettice, F., & Chung, S. H. (2011). The influence of greening the suppliers and green innovation on environmental performance and competitive advantage in Taiwan. *Transportation Research Part E: Logistics and Transportation Review*, 47(6), 822–836. <https://doi.org/10.1016/j.tre.2011.05.016>
- di Pietro, F., Bontempi, M. E., Palacin-Sanchez, M. J., & Samaniego-Medina, R. (2019). Capital structure across Italian regions: The role of financial and economic differences. *Sustainability*, 11(16), 4474. <https://doi.org/10.3390/su11164474>
- Filippini, M., & Hunt, L. C. (2015). Measurement of energy efficiency based on economic foundations [Article]. *Energy Economics*, 52, S5–S16. <https://doi.org/10.1016/j.eneco.2015.08.023>
- Fu, T. (2018). How does government intervention determine a Firm's fuel intensity: Evidence from China. *Journal of Cleaner Production*, 196, 1522–1531. <https://doi.org/10.1016/j.jclepro.2018.06.124>
- Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220–265. <https://doi.org/10.1080/07421222.2018.1440766>
- Herrerias, M. J., Cuadros, A., & Luo, D. (2016). Foreign versus indigenous innovation and energy intensity: Further research across Chinese regions. *Applied Energy*, 162, 1374–1384. <https://doi.org/10.1016/j.apenergy.2015.01.042>
- Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112(1), 116–135. <https://doi.org/10.1016/j.jfineco.2013.12.002>
- Hu, J.-L., & Wang, S.-C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy*, 34(17), 3206–3217. <https://doi.org/10.1016/j.enpol.2005.06.015>
- Huang, Z. H., Dong, H., & Jia, S. S. (2022). Equilibrium pricing for carbon emission in response to the target of carbon emission peaking. *Energy Economics*, 112, 106160. <https://doi.org/10.1016/j.eneco.2022.106160>
- Huang, Z. H., Liao, G. K., & Li, Z. H. (2019). Loaning scale and government subsidy for promoting green innovation. *Technological Forecasting and Social Change*, 144, 148–156. <https://doi.org/10.1016/j.techfore.2019.04.023>
- Islam, F., Shahbaz, M., Ahmed, A. U., & Alam, M. M. (2013). Financial development and energy consumption nexus in Malaysia: A multivariate time series analysis. *Economic Modelling*, 30, 435–441. <https://doi.org/10.1016/j.econmod.2012.09.033>
- Jalil, A., & Feridun, M. (2011). The impact of growth, energy and financial development on the environment in China: A cointegration analysis. *Energy Economics*, 33(2), 284–291. <https://doi.org/10.1016/j.eneco.2010.10.003>
- Li, T., Li, X., & Albitar, K. (2021). Threshold effects of financialization on enterprise R&D innovation: A comparison research on heterogeneity. *Quantitative Finance and Economics*, 5(3), 496–515. <https://doi.org/10.3934/QFE.2021022>
- Li, T., & Ma, J. (2021). Does digital finance benefit the income of rural residents? A case study on China. *Quantitative Finance and Economics*, 5(4), 664–688. <https://doi.org/10.3934/QFE.2021030>
- Li, T., Wen, J., Zeng, D., & Liu, K. (2022). Has enterprise digital transformation improved the efficiency of enterprise technological innovation? A case study on Chinese listed companies. *Mathematical Biosciences and Engineering : MBE*, 19(12), 12632–12654. <https://doi.org/10.3934/mbe.2022590>
- Li, W. C., Xu, J., Ostic, D., Yang, J. L., Guan, R. D., & Zhu, L. (2021). Why low-carbon technological innovation hardly promote energy efficiency of China? – Based on spatial econometric method and machine learning. *Computers & Industrial Engineering*, 160, 107566. <https://doi.org/10.1016/j.cie.2021.107566>
- Li, W., Sun, W., Li, G. M., Jin, B. H., Wu, W., Cui, P. F., & Zhao, G. H. (2018). Transmission mechanism between energy prices and carbon emissions using geographically weighted regression. *Energy Policy*, 115, 434–442. <https://doi.org/10.1016/j.enpol.2018.01.005>
- Li, Z., Huang, Z., & Failler, P. (2022). Dynamic correlation between crude oil price and investor sentiment in China: Heterogeneous and asymmetric effect. *Energies*, 15(3), 687. <https://doi.org/10.3390/en15030687>

- Li, Z., Li, L., & Chen, J. (2019). Effects of industrial structure, carbon right market and technological innovation on carbon emission reduction efficiency of provinces and regions. *Science and Technology Management Research*, 16(36), 79–90. <https://doi.org/10.3969/j.issn.1000-7695.2019.16.011>
- Liu, S., Shen, X., Jiang, T., & Failler, P. (2021). Impacts of the financialization of manufacturing enterprises on total factor productivity: Empirical examination from China's listed companies. *Green Finance*, 3(1), 59–89. <https://doi.org/10.3934/GF.2021005>
- Liu, X. J., Zhu, J. N., Guo, J. F., & Cui, C. N. (2021). Spatial association and explanation of China's digital financial inclusion development based on the network analysis method. *Complexity*, 2021, 1–13. <https://doi.org/10.1155/2021/6649894>
- Liu, Y., Li, Z. H., & Xu, M. R. (2020). The influential factors of financial cycle spillover: Evidence from China [Article]. *Emerging Markets Finance and Trade*, 56(6), 1336–1350. <https://doi.org/10.1080/1540496X.2019.1658076>
- Lv, C. C., Shao, C. H., & Lee, C. C. (2021). Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Economics*, 98, 105237. <https://doi.org/10.1016/j.eneco.2021.105237>
- Palacin-Sanchez, M. J., & Di Pietro, F. (2016). The role of the regional financial sector in the capital structure of small and medium-sized enterprises (SMEs). *Regional Studies*, 50(7), 1232–1247. <https://doi.org/10.1080/00343404.2014.1000290>
- Ramirez-Portilla, A., Cagno, E., & Trianni, A. (2014). Is innovation an enabler of energy efficiency? An exploratory study of the foundry sector. *Energy Procedia*. 61, 1191–1195. <https://doi.org/10.1016/j.egypro.2014.11.1051>
- Sadorsky, P. (2011). Financial development and energy consumption in Central and Eastern European frontier economies. *Energy Policy*, 39(2), 999–1006. <https://doi.org/10.1016/j.enpol.2010.11.034>
- Sha, R., Ge, T., & Li, J. Y. (2022). How energy price distortions affect China's economic growth and carbon emissions. *Sustainability*, 14(12), 7312. <https://doi.org/10.3390/su14127312>
- Su, Y. Y., Li, Z. H., & Yang, C. Y. (2021). Spatial interaction spillover effects between digital financial technology and urban ecological efficiency in China: An empirical study based on spatial simultaneous equations. *International Journal of Environmental Research and Public Health*, 18(16), 8535. <https://doi.org/10.3390/ijerph18168535>
- Tsou, H. T., & Chen, J. S. (2023). How does digital technology usage benefit firm performance? Digital transformation strategy and organisational innovation as mediators. *Technology Analysis & Strategic Management*, 35(9), 1114–1127. <https://doi.org/10.1080/09537325.2021.1991575>
- Wang, M. X., Gu, R., Wang, M., & Zhang, J. R. (2021). Research on the impact of finance on promoting technological innovation based on the state-space model. *Green Finance*, 3(2), 119–137. <https://doi.org/10.3934/GF.2021007>
- Wang, X. Y., Zhao, D. S., Zhang, L. L., Hu, H. Q., Ma, Y. D., & Ma, J. Y. (2021). Relations between upgrading of industrial structure, innovation of green technology and water environmental pollution: Estimation based on dynamic simultaneous equation. *Desalination and Water Treatment*, 218, 80–86. <https://doi.org/10.5004/dwt.2021.26946>
- Yao, Y., Hu, D., Yang, C., & Tan, Y. (2021). The impact and mechanism of Fintech on green total factor productivity. *Green Finance*, 3(2), 198–221. <https://doi.org/10.3934/GF.2021011>
- Zhang, J. (2008). Estimation of China's provincial capital stock (1952–2004) with applications. *Journal of Chinese Economic and Business Studies*, 6(2), 177–196. <https://doi.org/10.1080/14765280802028302>
- Zhou, P., Ang, B. W., & Zhou, D. Q. (2012). Measuring economy-wide energy efficiency performance: A parametric frontier approach [Article; Proceedings Paper]. *Applied Energy*, 90(1), 196–200. <https://doi.org/10.1016/j.apenergy.2011.02.025>
- Zhu, L., Luo, J., Dong, Q. L., Zhao, Y., Wang, Y. Y., & Wang, Y. (2021). Green technology innovation efficiency of energy-intensive industries in China from the perspective of shared resources: Dynamic change and improvement path. *Technological Forecasting and Social Change*, 170, 120890. <https://doi.org/10.1016/j.techfore.2021.120890>